

ENGAGE-DEM: A Model of Engagement of People with Dementia

Giulia Perugia, Marta Díaz-Boladeras, Andreu Català-Mallofré, Emilia I. Barakova, and Matthias Rauterberg

Abstract— One of the most effective ways to improve quality of life in dementia is by exposing people to meaningful activities. The study of engagement is crucial to identify which activities are significant for persons with dementia and customize them. Previous work has mainly focused on developing assessment tools and the only available model of engagement for people with dementia focused on factors influencing engagement or influenced by engagement. This paper focuses on the internal functioning of engagement and presents the development and testing of a model specifying the components of engagement, their measures, and the relationships they entertain. We collected behavioral and physiological data while participants with dementia (N=14) were involved in six sessions of play, three of game-based cognitive stimulation and three of robot-based free play. We tested the concurrent validity of the measures employed to gauge engagement and ran factorial analysis and Structural Equation Modeling to determine whether the components of engagement and their relationships were those hypothesized. The model we constructed, which we call the ENGAGE-DEM, achieved excellent goodness of fit and can be considered a scaffold to the development of affective computing frameworks for measuring engagement online and offline, especially in HCI and HRI.

Index Terms— Modelling human emotion, Nonverbal signals, Physiological measures, Health care, Social agents/robotics.



1 INTRODUCTION

DEMENTIA is an umbrella term for a set of neurodegenerative diseases that affect cognition, functioning, and psychosocial wellbeing (e.g., Alzheimer's Disease). It causes a reduction in thinking, problem-solving, and mnemonic ability, progressively impairs the self-care capability of a person, and often causes the emergence of disorders of perception, mood, and thought content called behavioral and psychological symptoms of dementia (BPSD; e.g., apathy, depression, anxiety) [1]. Several recent studies have underlined that quality of life (QoL) in dementia is not just driven by the progression of the disease and the incidence of BPSD [2][3], but is also worsened by social isolation [4] and lack of engagement [5][6][7]. According to the World Alzheimer Report [8], one of the most effective ways to improve QoL in dementia is by exposing people to meaningful and rewarding activities [9][10][11]. The study of engagement is hence crucial to identify those activities that are significant for the person with dementia and customize them.

Previous work has mostly focused on developing tools to assess engagement in dementia [12][13][14][15]. The only available model of engagement for dementia is the *Comprehensive Process Model of Engagement* [16], which fo-

cuses on the factors that influence engagement (i.e., personal, environmental, and stimulus attributes) and on those that are influenced by engagement (i.e., affect and behavior problems). The present paper aims at broadening the current knowledge on engagement in dementia by focusing on its internal functioning. In detail, it presents the development and testing of a model of engagement that specifies the components of engagement, how these can be measured in people with dementia, and which relationships they entertain. A proper formalization of the functioning of engagement can help designing architectures of sensors tracking engagement in real-time, thus automating the measurement of this state, and supporting the research on dementia and the work of caregivers and clinical staff. The online detection of engagement could help to adapt interactive technologies (e.g., social robots) to the user's affective state, thus making their use more enticing.

In the present study, we involved participants with dementia in two playful activities, a Game-Based Cognitive Stimulation (GBCS) and a Robot-Based Free Play (RBFP), and recorded their physiological and behavioral data with a wearable multi-sensor device (the E4 wristband [17]) and two hand-held cameras, respectively. Subsequently, we measured their engagement-related behavior with the Ethographic and Laban Inspired Coding System of Engagement (ELICSE) [18] and extracted features from their Electrodermal Activity (EDA) [19] and accelerometer signals [20]. The development of the ELICSE, and the suitability of EDA and accelerometer signals to assess engagement in dementia are discussed in previous work [18][19][20]. In this paper, we run a concurrent validity and factorial analysis to link these measures to the different components of engagement, and test our model of engagement, whose development is based on the extant literature, with Structural

- G. Perugia is with the Department of Information Technology, Uppsala University, Uppsala. E-mail: giulia.perugia@it.uu.se.
- M. Díaz-Boladeras and A. Català-Mallofré are with the Technical Research Centre for Dependency Care and Autonomous Living CETpD, Universitat Politècnica de Catalunya (UPC), Vilanova i la Geltrú (Barcelona). E-mails: marta.diaz@upc.edu and andreu.catala@upc.edu.
- E. I. Barakova and M. Rauterberg are with the Department of Industrial Design, Technische Universiteit Eindhoven (TU/e), Eindhoven. E-mails: e.i.barakova@tue.nl and g.w.m.rauterberg@tue.nl.

Equation Modeling (SEM).

In spite of being constructed around people with dementia, the applicability of this model can be extended to other user groups (e.g., children with autism, typically developed children) and other measurement techniques (e.g., eye-tracking), the main limitation being the type of activities assessed. These should have the following characteristics, they (a) should not entail *physical effort*, (b) should envision a *proactive role* for the user, and (c) should involve the use of *tangible artifacts* (being these traditional or technological). The model that we present can be thought of as a scaffold to support the development of affective computing frameworks for the online and offline measurement of engagement through nonverbal behavior and physiology. It is hence particularly suited to the fields of Human-Computer and Human-Robot Interaction (HCI and HRI).

The paper is organized as follows. In the section *Related Work*, we review the literature to identify definitions, components, and measures of engagement. In the section *Research Questions and Hypotheses*, we detail the questions that we addressed and the hypotheses we formulated on them. In the section *Methods and Materials*, we describe the methodology that we employed to collect a database of multimodal data while participants with dementia were involved in playful activities. In the section *Results and Discussion*, we present and discuss the concurrent validity of the measures of engagement we employed and the validation of the model. Last, in the section *Conclusions*, we summarize the contribution of this paper and outline possible future directions.

2. RELATED WORK

2.1. Definitions of Engagement

At present, there are many available definitions of engagement [21]. The literature is filled with partially overlapping notions called with different names and suited to different purposes and contexts: engagement, engrossment, immersion, enjoyment, and flow. The review that we performed returned a double definition of engagement. Engagement is described as the involvement with a task or activity, but also as the social interaction with an agent. We report both definitions of engagement, as they share similarities in their composition, and often co-exist in activities for people with dementia.

2.1.1 Engagement with a Task/Activity

One of the most prominent definitions of engagement with an activity is Csikszentmihalyi and LeFevre's definition of *flow* [22]. Flow is the way interviewees describe the experience of being engaged in autotelic activities [23]. As a state, flow entails an intense and focused concentration, the union of awareness and action, a sense of control of one's actions, the loss of self-consciousness, the distortion of the temporal axis, and the perception of intrinsic reward. Central to the notion of flow is the balance between *challenges* and *skills*. When a person is in flow, the activity is just manageable. The imbalance between challenges and skills can either lead to *anxiety* – when challenges exceed skills – or *apathy* – when skills exceed challenges.

Brown and Cairns [24] use the term *immersion* to describe a concept similar to flow, but not precisely overlapping, the experience of getting lost in a game and being out of contact with reality. According to the authors, immersion has three levels of intensity: *engagement*, *engrossment*, and *total immersion*. When engaged, gamers invest their time, effort, and attention in the game. When engrossed, their emotions are directly affected by the game. When totally immersed, they are cut off from reality, all that matters is the game. Douglas and Hargadon [25] also describe immersion, but in novels and films. In contrast with Brown and Cairns, who situated engagement in the continuum of intensity of immersion, they differentiate *engagement* from *immersion*: “immersive novels require virtually no engagement from their readers and viewers since they can simply follow the plot and enjoy the ride.” What this statement suggests is that engagement has to do with the proactive effort of the reader/viewer in the activity of reading/viewing, while immersion entails the act of being passively carried away by the novel/film.

In contrast with these views, engagement in dementia is mostly defined through its observable and tangible behavioral outcomes. Cohen-Mansfield et al. [16] define it as the “act of being occupied or involved with an external stimulus”, and, by extension, as “the antithesis of apathy;” Judge et al. [13] as the motor or verbal behavior exhibited in response to an activity. The behavioral nature of these definitions is due to the fact that the study of engagement in dementia has grown in importance in the last decade, especially thanks to the work of Cohen-Mansfield [26], and Moyle [27], but research has only recently focused on its more subjective and experiential aspects [28].

In conclusion, every reviewed definition of task/activity engagement includes the following elements: (a) a *person* – the user, the gamer, the reader, the viewer, (b) a *task/activity* – running, reading, playing games, watching films (c) the *allocation of the resources* of the person to the task/activity – attentional and affective resources, and (d) the *subjective experience* produced by the resource allocation. In the present paper, we are going to focus on activities that do not entail a physical effort, envision a proactive role for the person with dementia, and involve the use of tangible artifacts.

2.1.2 Engagement with an Agent

The definition of social engagement is rather settled and refined in the context of social sciences. One of its most eminent formalizations is Tickle-Degnen and Rosenthal's *rapport* [29]. According to the two authors, when people experience rapport, they are other-involved and form a cohesiveness with each other through the expression of *mutual attentiveness*. Also, they feel a mutual sense of friendliness and caring (i.e., *positivity*) and are fine-tuned with each other to the extent that they react simultaneously, sympathetically, and sometimes in a synchronized way (i.e., *coordination*), for instance, by mirroring each other's postures, gestures [30], and physiological states [31].

Engagement with an agent is a critical topic in HRI. However, as opposed to social sciences, HRI has not yet

developed a globally accepted definition of social engagement. Most of the studies regarding engagement with a social robot abstain from presenting a definition of engagement and rely on the reader's common sense to fill the void. Few of the definitions that can be retrieved are those of Sidner et al. [32], Rich et al. [33], Castellano et al. [34], and Díaz-Boladeras [35]. To these authors, engagement is: (i) "the process by which individuals in an interaction start, maintain, and end their perceived connection to one another" [32][33]; (ii) "the value that a participant in an interaction attributes to the goal of being together with the other participant(s) and continuing the interaction" [34]; and (iii) the observable component of bonding (e.g., time spent, joint activity, attention) and its behavior-inferred or self-reported emotional correlate (i.e., feeling of closeness) [35]. Due to the lack of a formal definition of social engagement in the context of social HRI, engagement is often confused with attention. However, as Castellano et al. [34] observe, engagement comprises an affective component on top of the attentional one.

Social engagement is always more central in the debate on QoL in dementia. Indeed, lack of meaningful social contact in people with dementia has been shown to speed up cognitive decline [36] and facilitate the occurrence of depression and apathy [37]. In the Comprehensive Process Model of Engagement, Cohen-Mansfield et al. [16] do not distinguish engagement with a task/activity from engagement in social interactions, and present sociality as an attribute of the stimulus. On the opposite, Jones et al. [14] define social engagement in dementia (in this case with a social robot) as a social connection/interaction, considering sociality as a quality of the interaction itself rather than of the stimulus.

In conclusion, the reviewed definitions of social engagement include the following elements: (a) a *person*, (b) a *social interaction* – human-human or human-robot, (c) the *allocation of the resources* of the person to the social interaction – attentional and affective resources, and (d) the *subjective experience* produced by the social interaction. According to this analysis, task/activity engagement and social engagement are structurally similar. They just differ in the target of their focus.

2.1.3 Co-activities

In activities for people with dementia, task/activity engagement and social engagement often co-exist. Indeed, most of the playful activities for people with dementia are carried out in dyads or groups. Brandtzæg et al. [38] call *co-activities* all those activities that imply a collective action. In these, users do not engage in a task/activity or a social interaction alone, but with one or more social partners. Co-activities are particularly important in dementia because a partner can provide *support* in situations of high strain [39], but could also act as a *scaffold* [40] showing less competent (or cognitively fit [41]) peers how to pursue the goals of the task/activity or social interaction. Given the common structure of task/activity engagement and social engagement and their co-presence in most of the playful activities for people with dementia, we are going to treat these two constructs as one in the remainder of the paper, but keep

differentiating them based on their target.

2.2 Components of Engagement

According to the literature, engagement is a compound of observable (i.e., attentional and affective resource allocation) and subjective elements (i.e., the subjective experience that derives from resource allocation). As the main focus of this paper is to develop a model of engagement that can be fully automated and measured in real-time, we are going to focus exclusively on the observable facet of engagement. As we saw, this regards resource allocation and is made of two elements: *attention* and *affect*. The next subsections are meant to describe attention and affect in engagement in more detail.

2.2.1 Attention

Attention is unanimously recognized as the essential component of engagement. Indeed, it appears in all the reviewed frameworks. Nakamura and Csikszentmihalyi [42] state that attention plays a crucial role in entering and staying in flow, as it shapes a person's experience. "What to pay attention to, how intensely, and for how long are choices that will determine the content of consciousness, and therefore the experiential information that is available to the organism" [43]. O'Brien and Toms [44] describe four steps of engagement all modulated by attention: (1) *point of engagement*, which occurs when the user's attention is drawn by the aesthetic qualities of a system, (2) *period of engagement*, which is the period of time during which the user maintains the attention on the system, (3) *disengagement*, which occurs when the user sways the attention from the system to direct it somewhere else, and (4) *re-engagement*, which happens when the user's attention is brought back to the system after a period of disengagement.

In the context of social engagement, attention can become mutual. This is because all participants in the interaction – being those persons or artificial agents (e.g., virtual agents, social robots) – can, at the same time, direct the attention *towards* others and receive attention *from* others [29][32][33]. Similar to task-directed attention, mutual attentiveness occurs as a process with a phase of establishment, maintenance, and end [32][33].

Attention is considered one of the main dimensions of engagement, also when it comes to dementia [16]. In this case, it is described as the amount of focus that the person pays to the stimulus in terms of gaze allocation, manipulation of the stimulus, and verbal behavior regarding the stimulus. In our framework of engagement, we adopt Csikszentmihalyi's definition of attention [45] both referring to attention toward a task/activity and toward an agent. According to this definition, attention – or *focused attention* – is the voluntary focusing of attention on a limited stimulus field (i.e., task/activity/social interaction).

2.2.2 Affect

In Csikszentmihalyi, affect is not a necessary condition of flow. However, most of the frameworks that we reviewed feature affect – of a positive nature – as a crucial dimension of engagement. Attfield et al. [46] and Chapman et al. [47] affirm that engaged users are affectively involved. Castellano et al. [34] and Peters et al. [48] regard

engagement as a compound of attention and affect. Douglas and Hargadon [25] talk about a pleasure principle embroidered in engagement. Brown and Cairns [24] present emotional involvement as the element discriminating between engagement and engrossment. O'Brien and Toms [44] describe an emotional thread built in the state of engagement. Last, Tickle-Degnen and Rosenthal [29] feature positivity as a component of rapport.

With regards to dementia, Cohen-Mansfield et al.'s framework of engagement [16] features an affective component, the *attitude* toward the stimulus. This is the amount of excitement and expressiveness towards the stimulus that the person with dementia displays. Also, Jones et al. [14] include an affective element in their conception of engagement in dementia. Indeed, they incorporate Lawtons' Observed Emotion Rating Scale (OERS) [49] in their Video Coding - Incorporating Observed Emotion. The OERS features negative and positive emotions (i.e., *pleasure, anger, anxiety/fear, sadness, and general alertness*).

In our framework of engagement, we borrowed Russell's definition of affect [50] as it is the most appropriate for a framework envisioning both behavioral and physiological assessment. According to Russell, affect - or *core affect* - is the neurophysiological state accessible to consciousness as a single simple feeling which a blend of two dimensions: *valence* - the pleasantness of the feeling- and *arousal* - the degree of activation that it entails.

2.3 Measurements of Engagement

Engagement can be measured on three different levels, according to three different response systems [51]: (i) *experiential/subjective*, which deals with the personal self-perceived experience of engagement, (ii) *behavioral/expressive*, which addresses the outer manifestation of engagement through behavior, and (iii) *peripheral-physiological*, which treats the physiological substrate of engagement. As the final purpose of our model of engagement is to support automation, we are mostly interested in the behavioral/expressive and peripheral-physiological levels. In recent years, research on dementia has also investigated the experiential/subjective level (i.e., self-reports) [52][53], and people with dementia have been involved in first person in designing assistive technologies [52]. Yet, a pilot study that we conducted in a nursing home faced us with the difficulty of participants to correctly remember the activities they took part in and retrieve how they felt during them. In order not to generate stress in participants, we decided to use observational rating scales, filled out by the clinical staff as a gold standard of engagement in the present study. These were the Observational Measurement of Engagement (OME) [12] and the Observed Emotion Rating Scale (OERS) [49].

Due to the incidence of BPSD such as apathy and depression in dementia (prevalence rates: apathy 55.5%; depression 44.9% [54]), the behavioral/expressive measurement level can also be impaired [55]. Persons with dementia might show blunted emotional reactions to activities. This is one of the reasons why it is crucial to enrich behavioral analysis with physiological data. To date, the peripheral-physiological level of assessment has been only rarely

studied in dementia. We attempt to fill this gap.

In the next sub-sections, we describe the main behavioral/expressive and peripheral-physiological measures of engagement. We leave aside the subjective/experiential measures because, as already discussed, they do not fall within the domain of interest of the present paper, nor did we use them as gold standard.

2.3.1 Behavioral/Expressive Measures

Most behavioral metrics of engagement for healthy subjects come from the field of social psychology (e.g., interaction studies on children) and social HRI. In this latter context, researchers look for behavioral indicators that robots can track and use to infer engagement states. In this sense, *gaze* is one of the most exploited behavioral cues of engagement [33][34][56][57] as it provides the robot with a clear idea of what the user is paying attention to.

Other extensively used behavioral cues of social engagement are *backchannel* events [29][33][58]. These are, for instance, nods and saying "uh, huh" and are typically used in conversation to notify the responder's comprehension of the initiator's communication. Also, *facial expressions* and *postures* are commonly used to quantify engagement. With regards to the first, the majority of the reviewed studies employ the Facial Action Coding System (FACS) [59] to recognize emotional facial expressions [34][60][61]. With regards to the latter, *posture actions* (e.g., sitting on the edge, leaning forward, sitting upright, leaning backward, slumping back), *joint kinematics* (i.e., the motion of joints or body segments), and *posture features* (i.e., body lean angle, slouch factor, quantity of motion, contraction index) are used to define engagement levels [60][62][63][64].

In the context of dementia, we identified two methodologies to assess engagement through behavior: (1) *observational rating scales*, which are Likert-type scales that gauge engagement on a number of items operationalized through behavior (i.e., OME and OERS) and (2) *ethograms* and *coding schemes*, which are respectively comprehensive and accurate inventories of actions observed in context and used to annotate videos (i.e., [49][14][16]) and excerpts of those aimed at answering specific research questions (i.e., [15]). Observational rating scales, ethograms, and coding schemes feature some of the behavioral metrics identified by social HRI. However, they take on a more exhaustive approach and also include *affective touch* (e.g., stroke, hold, tapping), *facial gestures* (e.g., kissing, yawning, wincing/grimacing), *manipulations* (e.g., hold, touch), *vocalizations* (e.g., singing, humming), *content of conversation* (e.g., yelling, cursing, berating), and *stereotyped and agitated behaviors* (e.g., hand-wringing, wandering) in the measurement of engagement.

In our previous work, we developed the ELICSE and the *Evidence-based MODEL of Engagement-related Behavior* (EMODEB) in the attempt to provide a systematic measurement framework of engagement-related behavior for dementia [18][65]. The ELICSE describes different behavioral modalities that could be used to assess engagement (gaze, postures, and arms/hands behavior), and clusters micro-behaviors into macro-labels based on the different

foci of the activity (i.e., game, partner, facilitator/experimenter, or none of them). The ELICSE is a modular coding system that can be down or upsized based on the peculiarities of the activities and persons whose engagement is to be assessed. The EMODEB, instead, describes and validates the hierarchical organization of the behaviors in the ELICSE, and accounts for engagement-related behavior as a whole (i.e., body configurations). It solves the fragmentation of the behavioral assessment tools of engagement, where multiple scores are obtained from annotations, and helps to obtain a unique score of engagement mindful of the expressive value and hierarchy of the different behavioral modalities.

In our previous work, we also found out that quantity of movement (QoMov), gauged through a wrist-worn tri-axial accelerometer can be used to assess engagement-related behavior in dementia [20]. The insight came from a number of studies using a wrist-worn actigraph (i.e., accelerometer) to diagnose apathy in dementia [66][67]. These discovered that people with apathy present a lower quantity of movement on the wrist. As arms/hands are used to manipulate objects and proactively participate in a task, we tested whether QoMov could increase as a consequence of engagement as much as it decreased due to apathy and depression, and demonstrated that this was the case.

In this study, we used the scores obtained from the ELICSE and EMODEB to measure the *valence* of engagement and the overall *attention* toward the activity, and the features of QoMov to gauge proactive *attention*.

2.3.2 Peripheral-Physiological Measures

As partially anticipated in section 2.3.2, our model of engagement leans on the *circumplex model of affect* [68]. This model describes affect as a two-dimensional space defined by two axes: a vertical axis – *arousal* – and a horizontal axis – *valence*.

Arousal can be assessed through a number of physiological measures. Among the others, heart rate (HR), heart-rate variability (HRV), pupil dilation, electroencephalography (EEG), and EDA. In spite of these multiple measurement possibilities, EDA – the electric change in the skin derived from the activation of the Sympathetic Nervous System (SNS) [69] – seems to be the most used [70][71]. The extensive use of EDA is to be ascribed to its low cost and minimal intrusiveness. Moreover, it is also due to the fact that EDA is more straightforward as a measure of engagement than cardiac measures (i.e., HR and HRV). Indeed, while the skin is exclusively innervated by the SNS, the heart is dually innervated by the SNS and the Parasympathetic Nervous System (PNS). As engagement can have an effect both on the SNS and the PNS, and each of these effects brings about an opposite physiological reaction of the heart (SNS > increased HR, PNS > decreased HR), the assessment of engagement through cardiac measures can lead to counterintuitive results [72]. Another measure of autonomic activation is pupil dilation [73], the increase in pupil diameter due to emotional stimulation. The main deterrent to the use of pupilometry in our study was the difficulty of keeping light conditions constant across sessions. As we collected data in nursing homes, the luminosity of

the room depended on the daily weather conditions. Unfortunately, we could not keep the set-up and light conditions of the room fixed without disrupting the workflow of the institutions.

There is a number of physiological measures that can be used to measure valence, too. Among the others, HRV and facial electromyography (EMG). HRV – which is the variation in the interval between heart-beats in a given time frame – is highly related to mental stress and negative valence [74]. *Facial EMG* – which is the electrical activity of the muscles of the face – is related to facial expressions of happiness (i.e., *zygomaticus major* and *orbicularis oculi*) and anger and sadness (i.e., *corrugator supercilii*) [75]. We decided to exclude HRV from our work as studies found that patients with dementia might show a decreased HRV [76][77]. With regards to facial EMG, we excluded it because its intrusiveness (i.e., electrodes are to be placed on participants' faces) was deemed unsuited to our target users and field data collection.

As a result of the review of the literature, we decided to employ EDA to assess *arousal*, and use the behaviors in the ELICSE, hierarchically organized as suggested by the EMODEB, to gauge *valence*. We presented exploratory results on the measurement of engagement-related arousal through EDA in [19]. In general, studies on the physiology of engagement of people with dementia are limited and mainly tackle the health benefits of engagement. They involve costly or invasive procedures that are not suited to field measurement: EEG [78], urinalysis and hormones analysis [79], and fNIRS [80]. The main antecedent to our work is a study carried out with healthy seniors and seniors with Mild Cognitive Impairment (MCI) during interactions with a telepresence robot (Giraff) using cardiac measures (i.e., HRV) [81].

3. RESEARCH QUESTIONS AND HYPOTHESES

In this work, we explore the following research questions:

- RQ1** Is there a good concurrent validity between the ELICSE, EDA, and QoMov [18][19][20] and the gold standard measures of engagement, OME and OERS [17][49]?
- RQ2** Are the relationships between the different components of engagement described by the literature supported by Structural Equation Modeling (SEM)?

As seen in Section 2, according to the literature, the components of engagement are *attention* and *affect*, with the latter being composed of *valence* (the pleasantness of an affective state) and *arousal* (the degree of activation that the affective state entails). As anticipated, in our model, we employ EDA to measure *arousal*, QoMov to gauge (proactive) *attention*, and the ELICSE to assess (overall) *attention* and *valence*. With regards to RQ1, we expect:

- H1.1** The behaviors of *attention* in the ELICSE to positively correlate with the item *attention* of the OME and/or with the item *general alertness* of the OERS
- H1.2** The behaviors of *valence* in the ELICSE to positively correlate with the items *attitude toward game*, *attitude toward partner* of the OME and/or with the item

pleasure of the OERS (and consequently to negatively correlate with the items *anger*, *anxiety/fear*, and *sadness* of the OERS)

H1.3 The features of *QoMov* to positively correlate with the item *attention* of the OME and/or with the item *general alertness* of the OERS

H1.4 The features of EDA to positively correlate with the items *attention*, *attitude toward game*, and *attitude toward partner* of the OME and/or with the items *pleasure* and *general alertness* of the OERS (and consequently to negatively correlate with the items *anger*, *anxiety/fear*, and *sadness* of the OERS)

It must be noted that, while the OME and OERS mainly assess *attention* and *valence*, EDA gauges *arousal*. Arousal varies as a result of attention and valence. However, there is no one-to-one correspondence between arousal, as measured via EDA, and attention and valence, as gauged with the OME and OERS, as should be the case in a test of concurrent validity. Unfortunately, we could not find a valid measure of *arousal* for people with dementia that we could use in the place of the OME and OERS.

With regards to RQ2, as previous studies stated that arousal can grow due to attentional processes [69], we hypothesized that:

H2.1 The components *attention* and *arousal* were positively correlated in our model of engagement

As attention is known to increase regardless of the direction of valence [50], we assumed that:

H2.2 The components *attention* and *valence* could be correlated as well as uncorrelated in our model

Finally, as arousal grows both as a consequence of attention and as a result of positive and negative valence [50], we postulated that:

H2.3 The components *arousal* and *valence* could be correlated as well as uncorrelated in our model

We describe the relationships between the components of engagement – *valence*, *arousal*, and *attention* – with correlations, instead of regressions, because we assume that the components of engagement can only rarely increase simultaneously. In the results section, we translate these hypotheses into path diagram notation and test them with SEM.

4. METHODS AND MATERIALS

4.1 Participants

To answer the research questions in section 3 and test the respective hypotheses, we ran an experimental study in two nursing homes in the province of Barcelona in Spain (*Redós de Sant Josep i Sant Pere* and *La Mallola*). *Inclusion criteria* for the participation in the study were a diagnosis of mild and moderate dementia and the informed consent of both the participants and their legal guardians (i.e., closest relative). *Exclusion criteria* were severe dementia, acute visual impairment, bedridden condition, reduced motility in the upper limbs, Parkinson’s disease, Parkinson’s disease dementia, and strong hallucinatory or delusional states. The selection of participants was performed by the clinical

staff of the nursing homes (i.e., psychologist and geriatrician) in three steps: (1) exclusion of residents with severe dementia and MCI, (2) exclusion of residents with Parkinson’s disease, Parkinson’s disease dementia, and motility issues in the upper limbs, and (3) exclusion of residents not willing to participate or sign the informed consent. Out of 17 participants that were found to comply with the inclusion and exclusion criteria, one refused to participate for a privacy concern, one fell ill immediately after being proposed the study, and one found it distressful to join the activity due to a severe form of agitation and wandering. The resulting 14 participants ($M_{age} = 83.93$; $SD_{age} = 7.28$) were screened with the *Mini-Examen Cognoscitivo* (MEC [82], the Spanish version of the Mini-Mental State Examination [83]), the Neuropsychiatric Inventory – Nursing Home version (NPI-NH [84]), and the Reisberg Global Deterioration Scale (Reisberg GDS [85]). All selected participants had a score of 4 or 5 at the Reisberg GDS (i.e., mild and moderate dementia), a score between 10 and 23 at the MEC (i.e., moderate to mild dementia), and a score inferior to 4 (i.e., the threshold for clinical significance) at the sub-items *delusions* and *hallucinations* of the NPI-NH. As the focus of the study was modeling engagement in co-activities, the 14 participants were randomly coupled and took part in the study in pairs. The participants in the couples did not know each other before the start of the study.

TABLE 1
OVERVIEW OF SESSIONS AND ORDER OF ACTIVITIES

Session 1	Session 2	Session 3	Session 4	Session 5	Session 6
Jigsaw 1		Dominoes		Shape 1	
Jigsaw 2		Jigsaw 1		Shape 2	
Jigsaw 3		Jigsaw 2		Shape 3	
Shape 1	Pleo	Jigsaw 3	Pleo	Dominoes	Pleo
Shape 2		Shape 1		Jigsaw 1	
Shape 3		Shape 2		Jigsaw 2	
Dominoes		Shape 3		Jigsaw 3	

4.2 Experimental Design

The study followed a repeated measures design and featured two activities as experimental conditions: a GBCS, and a RBFP. Each activity was presented in a different session and was repeated three times within the study (3 sessions per activity x 2 types of activity x 7 couples = 42 sessions). The sessions of GBCS (i.e., jigsaw puzzles, shape puzzles, domino) and RBFP were alternated in order and presented to participants every other session (see table 1).

All sessions of activities were conducted by a *facilitator* (i.e., psychologist or social educator) at the presence of an *experimenter* – always the same researcher from the university. The presence of the experimenter was functional to monitoring the equipment and helping facilitators in case of problems. To reduce participants’ reactivity, the experimenter took part in the activities of the two nursing homes for one month before the start of the study and was introduced to the participants as someone observing which activities they liked the most.

4.3. Activities

The activities constituting the experimental conditions of the study were chosen as they fitted in the definition of *co-activities*. Also, GBCS and RBFP differed in a number of aspects, they involved: (1) different *skills* (social and cognitive vs social and emotional), (2) different *degrees of challenge* (right or wrong activity vs failure-free activity), and (3) tangible artifacts with different *degrees of interactivity* (static artifacts vs interactive technologies) and different *interactive qualities* (non-social artifacts vs social artifacts). Thus, the two activities were likely to prompt engagement states with diverse characteristics, behavioral and physiological correlates. This was the ideal condition to test a model of engagement generalizable to further activities.

4.3.1 Game-based Cognitive Stimulation (GBCS)

In the *jigsaw puzzles*, the couples were asked to collaboratively assemble a set of pieces in a complete picture, usually of an animal. In the *shape puzzles*, they were requested to wedge a set of shapes, usually in wood, in a board with a series of slots. In the match with the tiles of *domino*, the players were requested to down a numbered tile from a set of seven that matched the tile on the table. The jigsaw puzzles and the shape puzzles to complete were three. They were presented in a progressive order of difficulty, from the easiest to the most difficult across sessions (see table 1). The challenge of the jigsaw puzzles was customized according to the cognitive level of participants. The right level of challenge for the different degrees of dementia severity was identified in a pilot study. With regard to the dominoes, all couples played one match with dominoes. The order of presentation of the three different board games was randomized using a Latin Squares technique and was always different across sessions (see table 1).



Fig. 1. Pleo, the robotic dinosaur

4.3.2 Robot-based Free Play (RBFP)

In the RBFP, the couples interacted with Pleo. Pleo is a robotic dinosaur developed by UGOBE, which acts as a living pet (see figure 1). It has an array of sensors that allow it to make sense of the surrounding environment and interact with people. For instance, touch sensors to discriminate among different types of touch, microphones to perceive sound and orientate towards it, ground foot sensors to detect surfaces, a camera-based vision system to detect light and navigate, and an internal clock to recognize the time to get up, eat, or sleep. Pleo is also able to display its

internal states (e.g., hunger, sleepiness) and moods (e.g., happy, scared). We chose Pleo among the available social robots because, while being very interactive and responsive, it featured a series of traits that are demonstrated to be appealing to older people [81]: it is small (in relation to human size), it has animal-like features, and its behavior mimics that of a domestic animal (e.g., cat and dog).

During sessions, participants interacted with Pleo in a spontaneous manner. However, due to the unstructured nature of the activity, the facilitators were given a list of activities that Pleo could support (e.g., feed Pleo, make Pleo sleep) so that they could prompt further interactions in case of a deadlock.

4.4 Data Acquisition

4.4.1 Video Cameras

All sessions were video recorded with two hand-held cameras positioned one in front and one on the side of participants. The video cameras were switched on as soon as participants reached the activity room and were switched off once they left the room after the activity. Each session lasted around 50 minutes, and the activities had a duration of ~20-25 minutes. As a result, we collected ~35 hours of video footage, half of which (~17.5 hours) were of activities. Albeit the presence of cameras can be thought of as a factor that could affect participants' behavior, we noticed that participants stopped paying attention to cameras once the activity started.



Fig.2. E4 wristband

4.4.2 E4 Wristband

We collected physiological signals with the E4 wristband (see figure 2). The E4 is a wearable multi-sensor device for real-time computerized biofeedback and data acquisition [17]. It has four sensors embedded in its case: (1) a *photoplethysmography* sensor (PPG) to measure blood volume pulse and derive HR, HRV, and inter-beat interval, (2) a *triaxial accelerometer* to capture motion-based activity and detect movement patterns, (3) an *infrared thermophile* to gauge peripheral skin temperature, and (4) an *EDA response sensor* to measure the electrical conductance of the skin. The E4 was selected among the available wearable sensors for its light weight and unobtrusiveness. It was also the only device measuring EDA that did not entail the positioning of electrodes on the medial or distal phalanges. This was of crucial importance as it left participants free to manipulate objects during activities without jeopardizing the data collection. In the context of this study, the E4 was employed to collect both the EDA and accelerometer data.

4.4.3 Setting and Procedure

The data collection was performed in the nursing homes, in rooms that were usually allocated to recreational activities. A rectangular table was placed on one side of the room. The frontal video camera was positioned on a small table facing the rectangular one, while the lateral video camera was either hidden on a library shelf or positioned on a desk. During activities, participants sat on the same side of the rectangular table, the facilitator stood up in-between them, and the experimenter sat on a chair close to the frontal camera. The sessions were made of six phases:

1. *Preparation phase* (~10 minutes): the experimenter set up the room, while the facilitator helped participants to reach it. Once participants reached the room, the experimenter switched on the video cameras
2. *Habituation phase* (~5 minutes): the experimenter and facilitator conversed with the participants, while they sat to recover from the effort of walking to the room, then s/he helped them to wear the E4 wristband
3. *Synchronization phase* (~2 minutes): the experimenter switched on the wristbands of both participants and simultaneously pushed the *tag* button on top of them to synchronize them with the video footage
4. *Baseline phase* (~5 minutes): the facilitator read a descriptive extract from a fairytale to the participants to collect the baseline of EDA
5. *Activity phase* (~20-25 minutes): the participants completed the three board games or interacted with Pleo
6. *End of the activity* (~5 minutes): the experimenter switched off the wristbands in front of the cameras, removed them, and turned off the cameras. At this point, the participants were guided back to their units.

In healthy adults and in lab environments, a relaxing film clip is usually employed to collect EDA at baseline [87]. However, this task did not fit the context of a nursing home and was a mismatch with the proposed activities. We ran a pilot data collection with four residents to establish a method for baseline collection. We obtained their EDA for 5 minutes in three conditions: while they rested in a common room, while they conversed with the clinical staff, and while they were read descriptive excerpts from fairytales. Participants had abrupt phasic responses in the first and second condition, mainly due to the events occurring in the surroundings (e.g., someone not feeling well) or to the conversation content (e.g., war, death of a loved one). Instead, while listening to fairytales, their EDA signal dropped and smoothed. The reading seemed to act as a distractor allowing participants to not focus on the environment and to relax.

4.5 Experimental Measures

4.5.1 OME and OERS

The observational rating scales of engagement employed as a gold standard in the study were the OME [16] and OERS [49]. With regards to the former scale, we used the items *attention* (four-point Likert scale, where 1 stands for *not attentive* and 4 for *very attentive*) and *attitude* (seven-point Likert scale, where 1 stands for *very negative* and 7 for

very positive), using the latter twice, to obtain scores regarding the attitude of participants *toward the game* and the attitude *toward the partner*. Moreover, we added a further item, *cognitive difficulty* (five-point Likert scale, where 1 stands for *not at all difficult* and 5 *very difficult*), present in further elaborations of the OME, to keep track of the level of challenge of the proposed activities. With regards to the OERS, we used it in its original version to rate the presence or intensity of five affective states on a five-point Likert scale (where 1 is *never* and 5 is *more than 5 minutes*): *pleasure*, *anger*, *anxiety/fear*, *sadness*, and *general alertness*. We asked facilitators to fill out one OME and one OERS for the RBFP, and one OME and one OERS for each game of the GBCS at the end of the sessions. We then computed the median of the three scores of the GBCS and used it for analyses.

TABLE 2
THE ELICSE: OVERVIEW OF BEHAVIORS AND MODIFIERS

HEAD BEHAVIORS	HEAD MODIFIERS
GAZE GAME (GG)	
GAZE PARTNER (GP)	
GAZE FACILITATOR/EXPERIMENTER (GFE)	<i>positive</i> gestural support (_pos) <i>no</i> gestural support (_no) <i>negative</i> gestural support (_neg)
NONE OF THE TARGET HEAD MOVEMENTS (NoH)	
TORSO BEHAVIORS	TORSO MODIFIERS
NEAR REACH/LEAN TOWARD GAME (NRLTG)	<i>positive</i> postural support (_pos) <i>no</i> postural support (_no) <i>negative</i> postural support (_neg)
LEAN IN PARTNER (LIP)	
NONE OF THE TARGET TORSO MOVEMENTS (NoT)	(none)
ARMS/HANDS BEHAVIORS	ARMS/HANDS MODIFIERS
MANIPULATE GAME (MG)	
REACH OUT PARTNER (RoP)	<i>positive</i> quality of gesture (_pos) <i>no</i> quality of gesture (_no) <i>negative</i> quality of gesture (_neg)
REACH OUT FACILITATOR/EXPERIMENTER (RoFE)	
POSITIVE SIGNS OF AFFECTION INVOLVING ARMS/HANDS (SoA_pos)	(none)
NEGATIVE SIGNS OF AFFECTION INVOLVING ARMS/HANDS (SoA_neg)	(none)
NONE OF THE TARGET ARMS/HANDS MOVEMENTS (NoAH)	(none)

The behaviors that can be further specified by modifiers are written in italics

4.5.2 ELICSE

As anticipated, in this study, we employed the ELICSE to measure engagement at a behavioral/expressive level [18]. The ELICSE is composed of behaviors and modifiers. The behaviors in the ELICSE measure changes in the direction of attention along three modalities: head (gaze), torso (postures), and arms/hands (see table 2). The modifiers define whether these changes have a positive, neutral, or negative value, or are accompanied by gestures having a positive, neutral, or negative value. For instance, stroke the ro-

bot or squeeze the robot's tail fall both in the behavior *manipulate game*, but the former can be categorized with the modifier *positive quality of gesture*, while the latter should be classified with *negative quality of gesture*. Likewise, one can *gaze toward partner* (behavior) while frowning (modifier *negative gestural support*) or smiling (modifier *positive gestural support*). Behaviors and modifiers in the ELICSE were measured as durations. For an overview of them, refer to table 2. For more information on the development of the ELICSE, and the operational descriptions, see [18].

TABLE 3
SET OF EDA FEATURES AND EQUATIONS

FEATURE	EQUATION
SMA EDA ^a	$\sum_{i=1}^T s_i^W dt - \sum_{i=1}^T s_i^{W(1)} dt$
MEAN EDA ^b	$\bar{s}^W - \bar{s}^{W(1)}$, where $\bar{s}^W = \frac{1}{N} \sum_{i=1}^N s_i^W$
STD EDA ^c	$\sigma s^W - \sigma s^{W(1)}$, where $\sigma s^W = \sqrt{\frac{1}{N} \sum_{i=1}^N (s_i^W - \bar{s}^W)^2}$
RNG EDA ^d	$Rng(s^W) - Rng(s^{W(1)})$, where $Rng(s^W) = \max(s^W) - \min(s^W)$
SUM H EDA ^e	$\sum_{i=1}^N S_{i,N}^W$
NPR EDA ^f	$NPR^W - NPR^{W(1)}$
KURT EDA ^g	$\delta_s^W - \delta_s^{W(1)}$, where $\delta_s^W = \frac{E \left[\left(S_{i,N}^W - S_{i,N}^{W(1)} \right)^4 \right]}{\left(E \left[\left(S_{i,N}^W - S_{i,N}^{W(1)} \right)^2 \right] \right)^2}$
SKEW EDA ^h	$\gamma_s^W - \gamma_s^{W(1)}$, where $\gamma_s^W = E \left[\frac{\left(S_{i,N}^W - S_{i,N}^{W(1)} \right)^3}{\sigma \left(S_{i,N}^W \right)} \right]$

a. SMA EDA= signal magnitude area of EDA; b. MEAN EDA= mean EDA; c. STD EDA= standard deviation of EDA; d. RNG EDA= range of EDA; e. SUM H EDA= summation of harmonics of EDA; f. NPR EDA= number of peaks ratio of EDA; g. KURT EDA= kurtosis of EDA; h. SKEW EDA= skewness of EDA

4.5.3 EDA

The set of EDA features to extract was compiled based on previous literature [88]. The feature notation in table 3 was constructed in the following way. The set of samples was recorded in a window of time defined by the beginning of the recording and the end of the activity (see 4.4.3). The Short Fast Fourier Transform of this set of samples was formed by S_1^W, \dots, S_N^W through (1):

$$S_h^W = \sum_{n=1}^N s_n e^{-i2\pi h \frac{n}{N}} \quad (1)$$

Where $h = 1, \dots, N$. S_h^W is a set of N complex numbers that represent the amplitude and phase of a harmonic. With regards to $Npeaks$, we denoted it as the number of significant local maxima found in SW . $NPRW$ is defined as $Npeaks(SW)$ divided by the length of SW .

Before feature extraction, the EDA signal was synchronized with the video footage to establish the beginning and end of the baseline phase, and the beginning and end of the activity phase. Then, it was normalized and denoised with a 2nd order Butterworth low pass filter with a cutoff frequency of 0.05 Hz. We extracted EDA features with Matlab from the *baseline phase - w(1)* - and the *activity phase - w*. To take into account the baseline state of the person with dementia, the values of the features extracted during baseline were subtracted from those of the features ex-

tracted during the activity phase (see table 3). Due to technical issues (e.g., failure to record or artifacts), we excluded 10 sessions. The final EDA dataset was hence composed of 74 sessions ($N_{GBCS}=34$; $N_{RBFP}=40$).

4.5.4 Quantity of Movement

In order to extract features from the accelerometer signal, we inputted in Matlab the same synchronization files used for EDA. With regards to the selection of accelerometer features, David et al. [66] and David et al. [67] did not extract features from the raw accelerometer signal but relied on the counts of supra-threshold movements on the wrist provided by an actigraph. We assumed that the most adequate accelerometer features of quantity of movement could be the signal magnitude area of the acceleration. This gauges the amount of variation in the accelerometer signal within a certain window. We extracted two features from the accelerometer signal: the signal magnitude area of the module of the three axes (SMA Acc_M) following equation (a) and the summation of the signal magnitude areas of the three axes (SMA Acc_S) as defined in equation (b). SMA Acc_M is related to the general quantity of movement, SMA Acc_S to the variability of movements.

$$SMA_M = \sum_{i=1}^T \sqrt{x_i^2 + y_i^2 + z_i^2} dt \quad (a)$$

$$SMA_S = \sum_{i=1}^T |x_i| dt + \sum_{i=1}^T |y_i| dt + \sum_{i=1}^T |z_i| dt \quad (b)$$

X_i, Y_i, Z_i are the acceleration of the X, Y, and Z axes in the i sample. T is the length of the window measured in number of samples. In the database of accelerometer signals, all sessions except one were valid ($N=83$). However, 14 sessions were collected on the dominant wrist due to problems encountered in collecting data on the non-dominant one (e.g., bruises due to dialysis). These sessions were excluded leading to 69 valid sessions ($N_{GBCS}=34$; $N_{RBFP}=35$).

4.6 Ethical Approval

The study was conducted according to the declaration of Helsinki and to Spanish laws number 159/2007 and 41/2002. An informed written consent was signed by all the legal guardians of participants. All participants were informed about the study and gave their consent to participate. Both the consent of the legal guardian and that of the participant were required to take part in the study.

5. RESULTS

5.1 Concurrent Validity of ELICSE

5.1.1 Data Reduction of ELICSE

To ascertain the concurrent validity of the ELICSE, we annotated all the videos in the database (42 videos, two participants per video) using Observer XT 10.5. We aggregated the behaviors and modifiers in the ELICSE as suggested by the EMODEB (see table 4) [18]. Behaviors directed toward the game and partner were considered as expressing attention and summed together. Behaviors directed towards the facilitator/experimenter or elsewhere were regarded as expressing lack of attention and added to each other. The latter were subtracted from the former.

The result was a score of attention for each behavioral modality comprised between -100 and 100 (i.e., *gaze toward activity*, *lean toward activity*, and *reach out activity*), where -100 represented the lowest and 100 the highest possible attention.

TABLE 4
AGGREGATION OF BEHAVIORS AND MODIFIERS IN THE ELICSE

BEHAVIORS	DATA REDUCTION
GAZE T. ACTIVITY (GAct)	(GP + GG) - (GFE + NoH)
LEAN T. ACTIVITY (LAct)	(LIP + NRLTG) - (NoT)
REACH OUT ACTIVITY (RoAct)	(RoP + MG) - (RoFE + NoAH)
MODIFIERS	DATA REDUCTION
GESTURAL SUPPORT (Gest Sup)	(GP_pos + GG_pos) - (GP_neg + GG_neg)
POSTURAL SUPPORT (Post Sup)	(LIP_pos + NRLTG_pos) - (LIP_neg + NRLTG_neg)
QUALITY OF GESTURE (QoGest)	(RoP_pos + MG_pos + SOA_pos) - (RoP_neg + MG_neg + SOA_neg)

A similar aggregation was performed for modifiers (see table 4). Negative modifiers (*negative gestural support*, *negative postural support*, and *negative quality of gesture*) were summed to each other, and we did the same with positive modifiers (*positive gestural support*, *positive postural support*, and *positive quality of gesture*). The former were subtracted from the latter (see *gestural support*, *postural support*, and *quality of gesture* in table 4). This way we obtained a negative score when negative valence was predominant, a positive score when positive valence was prevalent, and a score of zero when positive and negative valence were even.

Following [18], we also computed the weighted average of *gaze toward activity*, *lean toward activity*, and *reach out activity*, and the weighted average of *gestural support*, *postural support*, and *quality of gesture*. Before doing so, we transformed the values comprised between -100 and 100 into positive values comprised between 0 and 100. The weights were assigned based on the hierarchical ranking of the behavioral modalities in the EMODEB (.50 for head behaviors: *gaze toward activity* and *gestural support*; .40 for arms/hands behaviors: *reach out activity* and *quality of gesture*; and .10 for torso behaviors: *lean toward activity* and *postural support*). The result was a score for *attention* and *valence* ranging between 0 and 100.

5.1.2 Test of Concurrent Validity of ELICSE

As the items of the OME and OERS are ordinal, we performed a Spearman rank correlation (one-tailed, pairwise exclusion of cases, $N_{\text{GBCS}} = 42$, $N_{\text{RBFP}} = 42$) between them and the partial (i.e., *gaze toward activity*, *lean toward activity*, and *reach out activity*, and *gestural support*, *postural support*, and *quality of gesture*) and averaged scores of *attention* and *valence* obtained from the ELICSE. The results are displayed in table 5. *Gaze toward activity* and *reach out activity* were

significantly positively correlated with the item *attention* of the OME in both GBCS and RBFP. In RBFP, they were also significantly correlated with *general alertness*. These results confirm our predictions (see H1.1 in section 3) that the behaviors of attention in the ELICSE were significantly correlated with the items *attention* and *general alertness*.

On top of these expected results, we found other interesting ones. In RBFP, *gaze toward activity* was significantly positively correlated with the item *attitude toward game* of the OME, and *reach out activity* was significantly positively correlated with the items *attitude toward game* and *attitude toward partner* of the OME and *pleasure* of the OERS. Moreover, while, in GBCS, *lean toward activity* was significantly positively correlated with *pleasure*, in RBFP, it was close to significantly negatively correlate with the same item.

With regards to valence, *gestural support* was significantly positively correlated with the items *attitude toward game* and *attitude toward partner* of the OME and the item *pleasure* of the OERS in GBCS, while it was positively correlated with *attitude toward game* and *pleasure* in RBFP. *Quality of gesture* was significantly positively correlated with the item *pleasure* of the OERS in GBCS, whereas it was significantly positively correlated with the items *attitude toward game* of the OME and *pleasure* of the OERS in RBFP. Also, *postural support* was positively correlated with both *attitude toward game* and *pleasure* in RBFP, and it was close to reaching a significant positive correlation with *pleasure* in GBCS ($p = .053$). These results allow us to accept our hypothesis (see H.1.2 in section 3) that the behaviors of valence in the ELICSE were significantly positively correlated with the items *attitude toward game* and *attitude toward partner* of the OME and *pleasure* of the OERS. With regard to *anger*, *anxiety/fear*, and *sadness*, we did not perform any analysis, as these items did not vary enough in the database. The same holds for the item *cognitive difficulty* in RBFP which was constant (i.e., 1= not at all).

On top of the postulated results for valence, we also found out that *gestural support* was significantly negatively correlated with *cognitive difficulty* in GBCS and significantly positively correlated with *attention* in RBFP. In this latter activity, also *quality of gesture* achieved a significant positive correlation with *attention*.

The results of the correlations between the partial scores of attention and valence drawn from the ELICSE were confirmed by those of the weighted averages. Indeed, the averaged score of *attention* was significantly positively correlated with the item *attention* of the OME both in GBCS and in RBFP, and also with the item *general alertness* of the OERS in the latter activity. Likewise, the averaged score of *valence* was significantly positively correlated with the items *attitude toward game* of the OME and *pleasure* of the OERS in both activities, but also with *attitude toward partner* in GBCS. Again, also in this case, our hypotheses were correct and could hence be accepted. Interestingly, the averaged score of *attention* obtained from the ELICSE was also significantly positively correlated with *attitude toward game* in GBCS and with *attitude toward game*, *attitude toward partner* and *pleasure* in RBFP. Similarly, the average score of *valence* was positively correlated with the item *attention* in both GBCS and RBFP.

5.1.3 Discussion of Concurrent Validity ELICSE

Our predictions on the presence and direction of the significant correlations were correct. Indeed, the single and global scores of attention and valence were significantly positively correlated with the corresponding items of the OME and OERS. Unexpectedly, however, the scores of attention drawn from the ELICSE achieved a significant positive correlation not just with the items of attention of the

OME and OERS, but also with those of valence in RBFP. Likewise, the scores of valence achieved a significant positive correlation not just with the items of valence of the OME and OERS, but also with those of attention in both GBCS and RBFP. While these results indicate that, in the selected activities, the more attention increased, the more valence turned positive, such functioning cannot be generalized to engagement itself. Indeed, high attention can ap-

TABLE 5
RESULTS OF CONCURRENT VALIDITY: EDA, QoMOV, AND ELICSE

EDA		GAME-BASED COGNITIVE STIMULATION					ROBOT-BASED FREE PLAY					
N _{GBCS} = 34; N _{RBFP} = 40		Attention	Att. game	Att. partner	Cog. Diff.	Pleasure	General Alertness	Attention	Att. game	Att. partner	Pleasure	General Alertness
SMA EDA	<i>r</i> (<i>s</i>)	.007	.025	.021	.277	.159	-.080	.066	*.351	.191	**-.411	.224
	<i>p</i>	.485	.445	.454	.060	.189	.329	.342	.013	.118	.004	.082
MEAN EDA	<i>r</i> (<i>s</i>)	.080	-.151	-.029	-.140	.079	-.018	-.062	-.130	**-.416	.133	.004
	<i>p</i>	.329	.201	.437	.219	.331	.461	.353	.212	.004	.208	.491
STD EDA	<i>r</i> (<i>s</i>)	.008	-.017	.038	-.277	.221	-.089	-.108	-.175	*-.304	.039	-.055
	<i>p</i>	.483	.463	.417	.059	.109	.312	.254	.140	.028	.406	.368
RNG EDA	<i>r</i> (<i>s</i>)	.016	.097	.083	-.210	*.291	-.036	-.169	-.111	*-.264	.053	-.051
	<i>p</i>	.464	.295	.324	.120	.050	.422	.148	.247	.050	.372	.378
SUM H EDA	<i>r</i> (<i>s</i>)	.104	-.032	.045	-.168	.128	-.080	-.047	.011	-.222	.185	.134
	<i>p</i>	.283	.430	.402	.176	.240	.329	.388	.474	.084	.126	.204
NPR EDA	<i>r</i> (<i>s</i>)	-.063	-.263	-.086	.145	.041	-.195	-.006	*.279	.101	*.348	.018
	<i>p</i>	.363	.070	.317	.211	.411	.138	.485	.041	.268	.014	.456
KURT EDA	<i>r</i> (<i>s</i>)	-.177	-.054	-.141	-.268	-.062	*.302	*-.288	*-.280	-.146	-.230	-.009
	<i>p</i>	.162	.382	.216	.065	.366	.044	.036	.040	.184	.076	.478
SKEW EDA	<i>r</i> (<i>s</i>)	-.161	-.059	-.158	-.287	-.077	*.302	*-.318	*-.298	-.174	-.247	-.050
	<i>p</i>	.186	.371	.190	.053	.335	.044	.023	.031	.141	.062	.379
QoMOV		GAME-BASED COGNITIVE STIMULATION					ROBOT-BASED FREE PLAY					
N _{GBCS} = 34; N _{RBFP} = 35		Attention	Att. game	Att. partner	Cog. Diff.	Pleasure	General Alertness	Attention	Att. game	Att. partner	Pleasure	General Alertness
SMA AccM	<i>r</i> (<i>s</i>)	**-.407	**-.431	*.350	**-.451	.184	-.022	.221	***.522	.085	**-.462	.219
	<i>p</i>	.008	.005	.021	.004	.148	.450	.101	.001	.313	.003	.104
SMA AccS	<i>r</i> (<i>s</i>)	*.350	*.366	*.293	*-.372	.210	-.056	.212	***.518	.063	**-.473	.209
	<i>p</i>	.021	.017	.046	.015	.117	.377	.111	.001	.359	.002	.114
ELICSE (modalities)		GAME-BASED COGNITIVE STIMULATION					ROBOT-BASED FREE PLAY					
N _{GBCS} = 42; N _{RBFP} = 42		Attention	Att. game	Att. partner	Cog. Diff.	Pleasure	General Alertness	Attention	Att. game	Att. partner	Pleasure	General Alertness
GAct	<i>r</i> (<i>s</i>)	*.284	.202	.225	.048	-.089	.189	***.451	**-.399	.242	.121	**-.411
	<i>p</i>	.034	.099	.076	.382	.288	.115	.001	.004	.061	.223	.003
RoAct	<i>r</i> (<i>s</i>)	*.268	.180	.077	.103	.187	.069	**-.420	***.645	**-.409	***.561	*.302
	<i>p</i>	.043	.128	.314	.257	.118	.331	.003	>.001	.004	>.001	.026
LTAct	<i>r</i> (<i>s</i>)	.207	.153	.140	-.136	*.309	-.141	-.075	-.160	.045	-.237	-.192
	<i>p</i>	.094	.166	.188	.195	.023	.186	.319	.156	.389	.066	.111
GestSup	<i>r</i> (<i>s</i>)	**-.426	***.542	***.604	*-.343	***.683	-.041	**-.428	***.494	.039	***.619	.128
	<i>p</i>	.002	>.001	>.001	.013	>.001	.399	.002	>.001	.403	>.001	.210
QoGest	<i>r</i> (<i>s</i>)	.039	.148	.241	.041	***.477	-.073	*.272	***.506	.203	***.632	.145
	<i>p</i>	.403	.175	.062	.398	.001	.323	.041	>.001	.098	>.001	.180
PostSup	<i>r</i> (<i>s</i>)	-.180	-.121	-.027	.163	.252	.082	.255	***.460	.196	***.596	.116
	<i>p</i>	.126	.223	.433	.152	.053	.304	.051	.001	.106	>.001	.233
ELICSE (averaged)		GAME-BASED COGNITIVE STIMULATION					ROBOT-BASED FREE PLAY					
N _{GBCS} = 42; N _{RBFP} = 42		Attention	Att. game	Att. partner	Cog. Diff.	Pleasure	General Alertness	Attention	Att. game	Att. partner	Pleasure	General Alertness
attention	<i>r</i> (<i>s</i>)	*.378	*.261	.189	.068	.176	-.017	**-.439	***.542	**-.394	*.330	*.307
	<i>p</i>	.007	.048	.115	.335	.133	.458	.002	>.001	.005	.016	.024
valence	<i>r</i> (<i>s</i>)	**-.391	***.476	***.540	-.245	***.683	-.055	**-.423	***.568	.109	***.710	.110
	<i>p</i>	.005	.001	>.001	.059	>.001	.365	.003	>.001	.246	>.001	.244

Significance level: * $<.05$; ** $<.01$; *** $<.001$

pear with positive, but also with neutral and negative valence. Indeed, in this study, we observed episodes where attention was high (*gaze toward activity, lean toward activity, reach out activity*) but valence was negative (e.g., frowning and vigorously squeezing the robot's tail).

In terms of attention, two scores obtained from the ELICSE seemed to be the most crucial: *gaze toward game* and *reach out game*. The score *lean toward activity* appeared to be less critical. Moreover, it was significantly positively correlated with *pleasure* in GBCS and negatively (but not significantly) correlated with the same item in RBFP. This conflicting result can be explained with the fact that, while, in GBCS, *leaning toward the activity* almost always led to *reach out activity* and hence to positive affect, in RBFP, it did not always do so. When leaning toward the activity, the participants often lingered in a passive observation of the robot, which accounted for a less intense engagement.

In terms of valence, all the three scores obtained from the ELICSE were significantly positively correlated with the items of valence in the OME and OERS. However, in GBCS, with respect to RBFP, *gestural support* seemed to be more meaningful. This did not come as a surprise. Indeed, while in the interaction with a social robot, valence can be expressed through affective touch (e.g., stroke, pat, hug, and cradle the robot), in the play with board games, it rather involves facial expressions (e.g., smile, frown).

The last result that is worth discussing is the negative correlation between *gestural support* and *cognitive difficulty*. This points to the need to customize the challenges of activities to the cognitive deterioration of the person with dementia. Indeed, in line with [22], when challenges exceed skills, flow leaves space to *anxiety* and negative emotions.

5.2 Concurrent Validity EDA

5.2.1 Test of Concurrent Validity EDA

In order to determine the concurrent validity of EDA, we extracted the EDA features from all the valid sessions in the database. Then, we performed a Spearman rank correlation (one-tailed, pairwise exclusion of cases, $N_{GBCS}=34$; $N_{RBFP}=40$) between the features of EDA and the items of the OME and OERS. The results are displayed in table 5. In GBCS, we found only a few significant correlations: RNG EDA was significantly positively correlated with the item *pleasure*, and KURT EDA and SKEW EDA were positively correlated with the item *general alertness* of the OERS. On the contrary, in RBFP, the number of correlations between EDA features and the items of OME and OERS was more substantial. SMA EDA was significantly positively correlated with *attitude toward game* and *pleasure*. MEAN EDA, STD EDA, and RNG EDA were significantly negatively correlated with the item *attitude toward partner* of the OME. NPR EDA was significantly positively correlated with *attitude toward game* and *pleasure*. Last, KURT EDA and SKEW EDA were negatively correlated with the items *attention* and *attitude toward game* of the OME.

5.2.2 Discussion of Concurrent Validity EDA

Our hypotheses on the concurrent validity of EDA were hence supported only in RBFP (see section 3, H1.4). Indeed,

in this activity, the features of EDA were significantly positively correlated with the items of attention and valence of the OME and OERS. With regards to GBCS, the number of significant correlations was small. In general, EDA seemed to increase more as a result of valence than attention. This might explain why we found fewer correlations in GBCS than in RBFP. By observing the correlations that were close to reach significance in GBCS, we also noticed that tonic EDA (i.e., the slower acting component and background characteristics of the signal [87]) – represented by MEAN EDA, STD EDA, RNG EDA, and SUM H EDA – decreased with *cognitive difficulty* while it increased with *pleasure*. These opposite movements of the signal might have canceled out each other and caused the non-significant correlations in GBCS. In future studies, it would be useful to address this issue, and quantify to what extent cognitive vs. emotional processing influence EDA responses.



Fig. 3. EDA signal of the participant on the right. In the top image, EDA of the participant while she is interacting with the robot. In the bottom image, EDA of the participant while the partner is interacting with the robot

A somewhat counterintuitive result regarded the negative correlation between *attitude toward partner* and MEAN EDA and STD EDA in the RBFP. When the *attitude toward partner* increased, tonic EDA decreased (i.e., MEAN EDA, STD EDA, and RNG EDA). This result can be explained by contrasting it with participants' behavior. As the arousing element of RBFP was the robot, when participants directly interacted with it, arousal increased (see top image in figure 3). On the opposite, when participants did not directly interact with the robot but observed the partner interacting with it, arousal decreased (see bottom image in figure 3). This is a clear example of how the multilevel assessment of engagement could help to illuminate social dynamics that would otherwise go unnoticed.

Another peculiar result regards KURT EDA and SKEW EDA. These features were positively correlated with *general alertness* in GBCS and negatively correlated with *attention* in RBFP. This might have been due to the slightly different operationalization of *general alertness* and *attention*. However, while KURT EDA and SKEW EDA followed a similar pattern of correlation for *attention* in both activities (i.e., negative correlation), they did not follow the same pattern of correlation for *general alertness* across activities. Due to these conflicting results, we excluded KURT EDA and SKEW EDA from the final model of engagement.

5.3 Concurrent Validity QoMov

5.3.1 Test of Concurrent Validity QoMov

In order to verify the concurrent validity of QoMov, we extracted the accelerometer features from the valid sessions. Then, we ran a Spearman rank correlation (one-tailed, pairwise exclusion of cases, $N_{GBCS} = 34$; $N_{RBFP} = 35$) between the features of QoMov and the items of the OME and OERS. Both SMA Acc_M and SMA Acc_S were significantly positively correlated with the item *attention* of the OME in GBCS (see table 5). However, they were not positively correlated with *attention* nor with *general alertness* in RBFP, but rather with *attitude toward game* and *pleasure*. Similar correlations were present in GBCS, where SMA Acc_M and SMA Acc_S were also significantly positively correlated with the items *attitude toward game* and *attitude toward partner*. The last interesting result to mention is the negative correlation between the features of QoMov and the item *cognitive difficulty* of the OME in GBCS.

5.3.2 Discussion of Concurrent Validity QoMov

Overall, QoMov achieved concurrent validity both for GBCS and RBFP. In the latter activity, however, the correlations with the gold standard measures of engagement were not those expected (see section 3, H1.3). Indeed, while in GBCS, SMA Acc_M and SMA Acc_S were significantly correlated with the item *attention* of the OME, in RBFP, they were significantly correlated with the items of *valence*. This misalignment with our research hypotheses can be explained with the distribution of the behaviors of the ELICSE in the two different activities. Indeed, while in GBCS, arms/hands movements were directed toward the activity (i.e., *manipulate game* and *reach out partner*) on average 62.05% of the time, in RBFP, they were so 43.39% of the time. Of these 62.05% and 43.39%, .34% was positively valenced in GBCS (i.e., positive quality of gesture), while 20.68% was positively valenced in RBFP. This means that, in spite of being less prominent, attention was more positively valenced in RBFP, and justifies the correlations that we found. In line with the concurrent validity of the ELICSE, the positive correlations between the features of QoMov and the items of valence were present also in GBCS. This underlines once more that, in the two proposed activities, positive valence grew alongside attention.

Another interesting result regards *cognitive difficulty*. This not only had a negative effect on valence during GBCS (as we saw in section 5.1.3) but was also detrimental to proactive participation. When activities are perceived as too difficult, they not only elicit negative emotions but also

bring people with dementia to withdraw from them.

5.4 General Discussion

In conclusion, we can answer RQ1 by stating that we found concurrent validity between the ELICSE, EDA, and QoMov and the gold standard measures of engagement. Indeed, these assessment tools captured crucial aspects of engagement. However, the captured aspects changed with the very nature of each activity's engagement. For instance, in RBFP, as most attention had positive valence, the scores of attention obtained from the ELICSE correlated with both the items of attention and those of valence of the OME and OERS. In GBCS, instead, as the expression of positive valence was less overt and critical to the activity, proactive attention (QoMov) took a more positive value. For the same reason, the *attitude* items of the OME (toward game and partner) seemed to capture something more than simple valence. The results of concurrent validity highlight the difficulty of establishing boundaries between the different components of engagement, and the impossibility of gauging them in isolation.

In spite of EDA not achieving the expected results in GBCS, we feel confident enough to include it in the final model of engagement. Indeed, as specified in section 3, the OME and OERS were not direct measures of arousal, but rather of attention and valence.

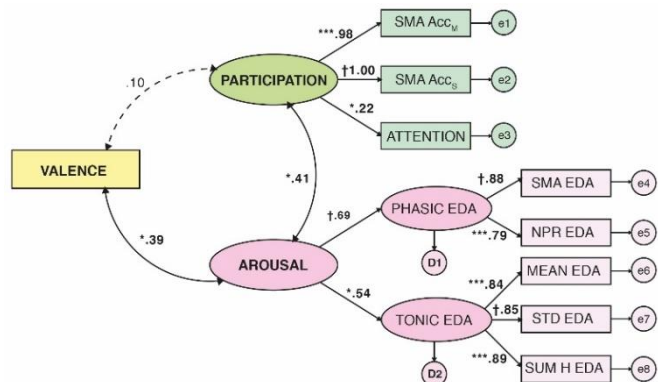


Fig. 4. The final model of engagement tested with SEM. † fixed factor, * < .05, ** < .01, *** < .001. Dotted covariance path: non-significant results

5.5 Model of Engagement

5.5.1 Structure of the Model

Once confirmed the concurrent validity of the ELICSE, EDA, and QoMoV, we proceeded to build and test the model of engagement. In agreement with the hypotheses on the functioning of engagement in section 3 (see H2.1, H2.2, and H2.3), we built the model in figure 4. In this model, three components of engagement are outlined: valence, arousal, and participation. *Valence* is the weighted average *valence* drawn from the ELICSE. *Arousal* is a latent variable assessed through the two components of EDA: tonic EDA and phasic EDA (i.e., faster changing elements of the signal, such as its peakedness [85]). *Tonic EDA* is gauged through the features MEAN EDA, STD EDA, and SUM H EDA, while *phasic EDA* through the features SMA EDA and NPR EDA. As can be seen, we did not include KURT EDA, SKEW EDA, and RNG EDA in the model.

With regards to the first two features, the reason behind this choice is discussed in section 5.2.2. With regard to the latter, RNG EDA was not a positive definite with STD EDA, thus it was considered redundant. Finally, *Participation* is a latent variable measured through the features of QoMov – SMA Acc_M and SMA Acc_S – and the weighted average *attention* coming from the ELICSE. We renamed attention as *participation* since its indicators (i.e., attention, SMA Acc_M, and SMA Acc_S) grasped the proactive participation in the activity. Inspired by Csikszentmihalyi’s definition of focused attention, we define *participation* as the voluntary focusing of attention on a limited stimulus field that is *proactively given* (e.g., active manipulation of an artifact or reaching out partner).

The relationships between the components of engagement *valence*, *arousal*, and *participation* are described with covariance paths in the model. We chose covariances rather than regressions as we assumed the three components of engagement could grow simultaneously only rarely (see H2.1, H2.2, and H2.3 in section 3). By connecting valence, arousal, and participation with covariances, we allowed *participation* and *arousal* to correlate positively, but, at the same time, we left *participation* and *valence*, and *arousal* and *valence* free to correlate (positively or negatively) or not.

TABLE 6
FACTOR LOADINGS AND CRONBACH’S ALPHA

FEATURE/SCORE	FACTOR LOADINGS*		
	1	2	3
SMA Acc _M	.959	.103	.141
SMA Acc _S	.959	.147	.104
ATTENTION	.422	.073	-.364
Cronbach’s α based on standardized item= .725			
STD EDA	-.050	.882	.190
SUM H. EDA	.061	.858	.310
MEAN EDA	.145	.885	.068
Cronbach’s α based on standardized item= .894			
SMA EDA	.094	.119	.893
NPR EDA	.149	.047	.881
Cronbach’s α based on standardized item= .815			
VALENCE	.044	.376	.213

In bold, factor loadings >.400

5.5.2 Testing of the Model

The model of engagement was tested with SEM with the software SPSS AMOS 22.0 using data from both activities. As we had a moderate amount of missing data for EDA and QoMov (see sections 4.5.3 and 4.5.4) and these data were missing completely at random (MCAR) [89][90], we used multiple regression imputation (5 imputations) to assign values to the missing cases [91]. Then, we calculated the sampling adequacy of the dataset (KMO= .662) and ran an exploratory factorial analysis (EFA) to confirm that the components in the final model were exactly those hypothesized. This was done with a principal component method of extraction and a varimax method of rotation. The EFA showed satisfying factor loadings for all indicators. We found three factors (see table 6). Factor 1 (i.e., *participation*) included SMA Acc_M, SMA Acc_S, and *attention*. Factor 2 (i.e., *tonic EDA*) included STD EDA, SUM H EDA, and MEAN

EDA. Last, factor 3 (i.e., *phasic EDA*) included SMA EDA and NPR EDA. *Valence* was not grouped under any of these factors. Then, we calculated the Cronbach’s alpha coefficients for each of the factors highlighted by the EFA. All factors achieved an alpha higher than .70, which is the cut-off score for reliability (see table 6).

TABLE 7
PATH ESTIMATES OF THE ENGAGE-DEM

REGRESSION PATH	EST.	S.E.	C.R.	p
PARTICIPATION → SMA ACC _M	.976	.008	39.06	***<.001
PARTICIPATION → SMA ACC _S	†1.000	/	/	/
PARTICIPATION → ATTENTION	.225	56.74	2.026	*=.043
AROUSAL → PHASIC EDA	†.694	/	/	/
AROUSAL → TONIC EDA	.536	94.90	2.184	*=.029
PHASIC EDA → SMA EDA	†.875	/	/	/
PHASIC EDA → NPR EDA	.787	1174.13	4.149	***<.001
TONIC EDA → MEAN EDA	.840	.255	8.674	***<.001
TONIC EDA → STD EDA	†.846	/	/	/
TONIC EDA → SUM H. EDA	.886	.158	9.112	***<.001
COVARIANCE PATH	EST.	S.E.	C.R.	p
AROUSAL ↔ PARTICIPATION	.405	.000	2.238	*=.025
PARTICIPATION ↔ VALENCE	.099	.010	.866	=.386
VALENCE ↔ AROUSAL	.388	.000	2.126	*=.031

Est.= Estimation; S.E.= Standard Error; C.R.= Critical Ratio; † fixed factor, *< .05, **< .01, ***< .001

We ran the model of engagement using SEM. To keep a good sampling adequacy, we performed the test of the model using data from both activities. The model proved to be an excellent fit for the data ($X^2(24, N= 84)= 30.793, p= .160; RMSEA= .058; NFI= .937; CFI= .985; RFI= .906, PNFI= .625$) and all the regression paths leading to the observed variables were significant (see table 7). With regards to the relationships between components:

1. *Participation* was significantly positively correlated with *arousal* ($r(82) = .405, p=.025$)
2. *Participation* was not significantly correlated with *valence* ($r(82) = .099, p=.386$)
3. *Valence* was significantly positively correlated with *arousal* ($r(82) = .388, p=.031$)

5.5.3 Discussion of the Model

In summary, the EFA confirmed that the components of engagement were those we hypothesized: *participation*, *valence*, and *arousal*. The test of the model through SEM enabled us to prove that the ELICSE, EDA, and QoMov were suitable tools to assess the components of engagement. Indeed, the factor loadings in the model were all significant and, with the exception of attention, quite strong. Also, SEM allowed us to define the relationships between the three components of engagement in the two activities, GBCS and RBFP. These were in line with our main vision of the functioning of engagement (see section 3). In conclusion, we can give a positive answer to RQ2. Indeed, our assumptions on the relationships between the different components of engagement were supported by the test of the model.

With regards to the low factor loading of the regression path leading to attention, this might be due to the fact that SMA Acc_M and SMA Acc_S are continuous variables, while *attention* is a ratio variable. Also, while QoMov exclusively refers to the active participation in the activity, *attention* incorporates both passive observation (i.e., gaze and postures) and active participation in the activity.

Concerning the significant positive correlation between valence and arousal, this points to the fact that, in these activities, when participation had positive valence, it grew together with arousal. With regards to the lack of a significant correlation between participation and valence, this seems to refute the positive correlations between the single and global scores of attention drawn from the ELICSE and the items of valence in the OME and OERS, and between the features of QoMov and the items of valence in the OME and OERS. However, we need to take into account that participation does not overlap with the single and global scores of attention nor with QoMov, but incorporates both, and that in the two activities under study the measures of attention and valence in the model partially overlapped (see section 5.4).

We call the model of engagement that we deployed in this paper ENGAGE-DEM. The ENGAGE-DEM is a model that outlines the components of engagement, describes how these can be measured and formalizes their relationships. In agreement with the findings of this paper, we would like to present a new definition of engagement. Engagement is the *degree of participation* in a playful activity that can take different *hedonic tones* (negative to positive valence) and achieve different levels of *energy mobilization* (low to high arousal).

The ENGAGE-DEM can be thought of as a support to develop affective computing frameworks for the automatic detection of engagement in people with dementia. In fact, the behaviors in the ELICSE can be collected via sensing technologies as much as the features of EDA and QoMov [92]. Gaze behaviors can be tracked with remote eye-trackers, action units accounting for emotional facial expressions can be recorded with Intel RealSense RGB-D cameras, and postures can be estimated with Microsoft Kinect sensors. Further research is needed to apply the model to real-world settings. Nevertheless, despite being developed for people with dementia, thanks to its comprehensiveness and scalability, the ENGAGE-DEM can be used with other user groups (e.g., children with autism) and envision different assessment techniques for its components.

5.6 Limitations and Future Work

The main limitations of this study reside in the small sample size, its geographical uniformity, and the presence of missing data. Future work should attempt to include a higher number of participants coming from diverse geographic backgrounds. Given the amount of structuring that the collection of multimodal data entails, one of the possible solutions to this problem is to work in transnational networks and collect data using common procedures. Another limitation of this research lies in the narrow range of activities and dementia groups used to test the model. Future work should validate the model and test our

hypotheses on the relationships between its components on more activities and multiple dementia groups (e.g., MCI). Also, we encourage replication with healthy subjects to verify the scope of application of the model. We also need to underline that, while considering the two activities together guaranteed a good sample size for SEM, it might have caused the cancellation of some of the dynamics characterizing engagement in the single activities.

Further limitations regard the OME and OERS. These were filled out by the same facilitators who conducted the activities rather than by external observers. The first-person involvement of facilitators in the activity might have hindered their capability to carefully observe participants' target behavior.

The measures of engagement we employed in this paper have limitations as well. For instance, EDA is extremely prone to noise and artifacts. This might be caused by participants touching the E4 wristband during activities and provoking the detachment of electrodes from the skin surface. Regarding QoMov, more work is needed to specify which thresholds define proactive engagement in different activities. Future work should also focus on translating the lengthy scoring of behavior in the ELICSE into automatic tracking. As a side note, the use of wearables with people with dementia is not straightforward and poses questions of acceptance and adoption that go beyond the scope of this paper, but need to be further studied.

As already mentioned, the ENGAGE-DEM cannot be applied to all activities, but only to those that entail proactive participation, do not involve physical effort, and requires tangible artifacts. This makes it particularly suited to HCI and HRI but excludes from its scope of application other activities, such as dance therapy and music therapy.

6. CONCLUSIONS

In this paper, we described and tested a model of engagement that identifies the components of engagement (participation, valence, and arousal), describes how these can be measured with existing assessment tools (ELICSE, EDA, and QoMov), and defines (and partially validates) the relationships that they entertain with each other. The model we propose, which we call the ENGAGE-DEM, represents the first formalization of the internal functioning of engagement for people with dementia and could be used to support the development of affective computing frameworks for HCI and HRI.

ACKNOWLEDGMENT

This work was supported by the joint doctorate in Interactive and Cognitive Environments (ICE) funded by Erasmus Mundus under the FPA 2010-2012. We thank the nursing homes *Redòs de Sant Josep i San Pere* and *La Mallola* for their precious collaboration.

REFERENCES

- [1] Finkel, S. (2000). Introduction to behavioural and psychological symptoms of dementia (BPSD). *International Journal of Geriatric Psychiatry*, 15(S1), S2-S4.

[2] Logsdon, R. G., Gibbons, L. E., McCurry, S. M., & Teri, L. (1999). Quality of life in Alzheimer's disease: patient and caregiver reports. *Journal of Mental Health and Aging*, 5(1), 21-32.

[3] Beerens, H. C., Zwakhalen, S. M., Verbeek, H., Ruwaard, D., & Hamers, J. P. (2013). Factors associated with quality of life of people with dementia in long-term care facilities: a systematic review. *International Journal of Nursing Studies*, 50(9), 1259-1270.

[4] Moyle, W., Venturto, L., Griffiths, S., Grimbeek, P., McAllister, M., Oxlade, D., & Murfield, J. (2011). Factors influencing quality of life for people with dementia: A qualitative perspective. *Aging & Mental Health*, 15(8), 970-977.

[5] Bryant, L. L., Corbett, K. K., & Kutner, J. S. (2001). In their own words: a model of healthy aging. *Social Science & Medicine*, 53(7), 927-941.

[6] Ritchey, L. H., Ritchey, L. H., & Dietz, B. E. (2001). Clarifying the measurement of activity. *Activities, Adaptation & Aging*, 26(1), 1-21.

[7] Lysack, C. L., & Seipke, H. L. (2002). Communicating the occupational self: A qualitative study of oldest-old American women. *Scandinavian Journal of Occupational Therapy*, 9(3), 130-139.

[8] Alzheimer's Disease International. (2019). *World Alzheimer Report 2019: Attitudes to dementia*. London: Alzheimer's Disease International.

[9] Brooker, D. J., Woolley, R. J., & Lee, D. (2007). Enriching opportunities for people living with dementia in nursing homes: an evaluation of a multi-level activity-based model of care. *Aging and Mental Health*, 11(4), 361-370.

[10] Kolanowski, A., Buettner, L., Litaker, M., & Yu, F. (2006). Factors that relate to activity engagement in nursing home residents. *American Journal of Alzheimer's Disease & Other Dementias*, 21(1), 15-22.

[11] van der Ploeg, E. S., Eppingstall, B., Camp, C. J., Runci, S. J., Taffe, J., & O'Connor, D. W. (2013). A randomized crossover trial to study the effect of personalized, one-to-one interaction using Montessori-based activities on agitation, affect, and engagement in nursing home residents with dementia. *International Psychogeriatrics*, 25(4), 565-575.

[12] Cohen-Mansfield, J., Dakheel-Ali, M., & Marx, M. (2009). Engagement in persons with dementia: The concept and its measurement. *The American Journal of Geriatric Psychiatry*, 17(4), 299-307.

[13] Judge, K., Camp, C., & Orsulic-Jeras, S. (2000). Use of Montessori-based activities for clients with dementia in adult day care: Effects on engagement. *American Journal of Alzheimer's Disease*, 15(1), 42-46.

[14] Jones, C., Sung, B., & Moyle, W. (2015). Assessing engagement in people with dementia: a new approach to assessment using video analysis. *Archives of Psychiatric Nursing*, 29(6), 377-382.

[15] Jøranson, N., Pedersen, I., Rokstad, A. M. M., Aamodt, G., Olsen, C., & Ihlebæk, C. (2016). Group activity with Paro in nursing homes: systematic investigation of behaviors in participants. *International Psychogeriatrics*, 28(8), 1345-1354.

[16] Cohen-Mansfield, J., Marx, M. S., Freedman, L. S., Murad, H., Regier, N. G., Thein, K., & Dakheel-Ali, M. (2011). The comprehensive process model of engagement. *The American Journal of Geriatric Psychiatry*, 19(10), 859-870.

[17] Garbarino, M., Lai, M., Bender, D., Picard, R. W., & Tognetti, S. (2014). Empatica E3 - A wearable wireless multi-sensor device for real-time computerized biofeedback and data acquisition. In *Wireless Mobile Communication and Healthcare (MobiHealth)*, 2014 EAI 4th International Conference on (pp. 39-42). IEEE.

[18] Perugia, G., van Berkel, R., Díaz-Boladeras, M., Català-Mallofré, A., Rauterberg, M., & Barakova, E. (2018). Understanding engagement in dementia through behavior. The Ethographic and Laban-Inspired Coding System of Engagement (ELICSE) and the Evidence-Based Model of Engagement-Related Behavior (EMODEB). *Frontiers in Psychology*, 9, 690.

[19] Perugia, G., Rodríguez-Martín, D., Díaz-Boladeras, M., Català-Mallofré, A., Barakova, E., & Rauterberg, M. (2017). Electrodermal activity: Explorations in the psychophysiology of engagement with social robots in dementia. In *26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)* (pp. 1248-1254). IEEE.

[20] Perugia, G., Rodríguez-Martín, D., Díaz-Boladeras, M., Català-Mallofré, A., Barakova, E., & Rauterberg, M. (2017). Quantity of movement as a measure of engagement for dementia. The influence of motivational disorders. *American Journal of Alzheimer's Disease and Other Dementias*, 33(2), 112-121.

[21] Doherty, K., & Doherty, G. (2019). Engagement in HCI: conception, theory and measurement. *ACM Computing Surveys (CSUR)*, 51(5), 99.

[22] Csikszentmihalyi, M., & LeFevre, J. (1989). Optimal experience in work and leisure. *Journal of Personality and Social Psychology*, 56(5), 815-822.

[23] Csikszentmihalyi, M. (1975). Play and intrinsic rewards. *Journal of Humanistic Psychology*, 15(3), 41-63.

[24] Brown, E., & Cairns, P. (2004). A grounded investigation of game immersion. In *CHI'04 Extended Abstracts on Human Factors in Computing Systems* (pp. 1297-1300). ACM.

[25] Douglas, Y., & Hargadon, A. (2000). The pleasure principle: immersion, engagement, flow. In *Proceedings of the 11th ACM on Hypertext and Hypermedia* (pp. 153-160). ACM.

[26] Cohen-Mansfield, J., Marx, M. S., Dakheel-Ali, M., Regier, N. G., & Thein, K. (2010). Can persons with dementia be engaged with stimuli? *The American Journal of Geriatric Psychiatry*, 18(4), 351-362.

[27] Jones, C., Sung, B., & Moyle, W. (2018). Engagement of a Person with Dementia Scale: Establishing content validity and psychometric properties. *Journal of Advanced Nursing*, 74(9), 2227-2240.

[28] Robillard, J. M., & Feng, T. L. (2017). When patient engagement and research ethics collide: lessons from a dementia forum. *Journal of Alzheimer's Disease*, 59(1), 1-10.

[29] Tickle-Degnen L. (2006) Nonverbal behavior and its functions in the ecosystem of rapport. In: Manusov V, Patterson M (eds) *The SAGE Handbook of Nonverbal Communication*. Thousand Oaks, California: Sage.

[30] La France, M., & Ickes, W. (1981). Posture mirroring and interactional involvement: Sex and sex typing effects. *Journal of Nonverbal Behavior*, 5(3), 139-154.

[31] Järvelä, S., Kivikangas, J. M., Kätsyri, J., & Ravaja, N. (2014). Physiological linkage of dyadic gaming experience. *Simulation & Gaming*, 45(1), 24-40.

[32] Sidner, C. L., Lee, C., Kidd, C. D., Lesh, N., & Rich, C. (2005). Explorations in engagement for humans and robots. *Artificial Intelligence*, 166(1-2), 140-164.

[33] Rich, C., Ponsler, B., Holroyd, A., & Sidner, C. L. (2010). Recognizing engagement in human-robot interaction. In *Proceedings of the 5th ACM/IEEE international conference on Human-Robot Interaction (HRI)* (pp. 375-382). ACM/IEEE.

[34] Castellano, G., Pereira, A., Leite, I., Paiva, A., & McOwan, P. W. (2009). Detecting user engagement with a robot companion using task and social interaction-based features. In *Proceedings of the 2009 International Conference on Multimodal Interfaces - ICM/MLMI '09* (pp. 119-126). ACM.

[35] Díaz-Boladeras, M. (2017) *Bonding with robotic pets. Children's cognitions, emotions and behaviors towards pet-robots. Applications in a robot assisted quality of life intervention in a pediatric hospital*. Barcelona: University of Barcelona (doctoral thesis).

[36] Hughes, T. F., Flatt, J. D., Fu, B., Chang, C. C. H., & Ganguli, M. (2013). Engagement in social activities and progression from mild to severe cognitive impairment: the MYHAT study. *International Psychogeriatrics*, 25(4), 587-595.

[37] Stoner, C. R., Orrell, M., & Spector, A. (2018). The Positive Psychology Outcome Measure (PPOM) for people with dementia: Psychometric properties and factor structure. *Archives of Gerontology and Geriatrics*, 76,

- 182-187.
- [38] Brandtzaeg, P. B., Følstad, A., & Heim, J. (2003). Enjoyment: lessons from Karasek. In Blythe, M. A., Overbeeke, K., Monk, A. F., Wright, P. C. (Eds.), *Funology: From Usability to Enjoyment* (pp. 56- 65). Dordrecht: Springer.
- [39] Karasek, R. & Theorell, T. (1990). Healthy work: Stress, productivity, and the reconstruction of working life. *The American Journal of Public Health*, 80, 1013-1014.
- [40] Vygotsky, L. (1987). *Mind in society: The development of higher psychological processes*. Cambridge, Massachusetts: Oxford University Press.
- [41] Gilkey, R., & Kilts, C. (2007). Cognitive fitness. *Harvard business review*, 85(11), 53.
- [42] Nakamura, J., & Csikszentmihalyi, M. (2009). Flow theory and research. In S. Lopez & C. Snyder (Eds.), *Oxford Handbook of Positive Psychology* (pp. 195-206). New York, New York: Oxford University Press.
- [43] Csikszentmihalyi, M. (1978). Attention and the holistic approach to behavior. In Pope, K. S. & Singer, J. L. (Eds.), *The stream of consciousness* (pp. 335-358). New York, New York: Plenum.
- [44] O'Brien, H. L., & Toms, E. G. (2008). What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the American Society for Information Science and Technology*, 59(6), 938-955.
- [45] Csikszentmihalyi, M. (2014). *Flow and the Foundations of Positive Psychology*. Dordrecht: Springer.
- [46] Attfield, S., Kazai, G., & Lalmas, M. (2011). Towards a science of user engagement (Position Paper). In *WSDM Workshop on User Modelling for Web Applications* (pp. 9-12). ACM.
- [47] Chapman, P., Selvarajah, S., & Webster, J. (1999). Engagement in multimedia training systems. In *Proceedings of the 32nd Annual Hawaii International Conference on Systems Sciences, 1999. HICSS-32* (pp. 1-9). IEEE.
- [48] Peters, C., Asteriadis, S., Karpouzis, K., & de Sevin, E. (2008). Towards a real-time gaze-based shared attention for a virtual agent. In *Workshop on Affective Interaction in Natural Environments (AFFINE), ACM International Conference on Multimodal Interfaces (ICMI'08)* (pp. 574-580). ACM.
- [49] Lawton, M. P., Van Haitsma, K., & Klapper, J. (1996). Observed affect in nursing home residents with Alzheimer's disease. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 51(1), 3-14.
- [50] Russell, J. (2003). Core affect and the psychological construction of emotion. *Psychological Review*, 110(1), 145-172.
- [51] Bradley, M. M., & Lang, P. J. (2000). Measuring emotion: Behavior, feeling, and physiology. In R. D. Lane, & L. Nadel (Eds.), *Cognitive Neuroscience of Emotion* (pp. 242-276). New York, New York: Oxford University Press.
- [52] Lindsay, S., Jackson, D., Schofield, G., & Olivier, P. (2012, May). Engaging older people using participatory design. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1199-1208). ACM.
- [53] Perfect, D., Griffiths, A. W., Vasconcelos Da Silva, M., Lemos Dekker, N., McDermid, J., & Surr, C. A. (2019). Collecting self-report research data with people with dementia within care home clinical trials: Benefits, challenges and best practice. *Dementia*, 1471301219871168.
- [54] Robert, P. H., Verhey, F. R., Byrne, E. J., Hurt, C., De Deyn, P. P., Nobili, F., Riello, R., Rodriguez, G., Frisoni, G., Tsolaki, M., Kyriazopoulou, N., Bullock, R., Burns, A., & Vellas, B. (2005). Grouping for behavioral and psychological symptoms in dementia: clinical and biological aspects. Consensus paper of the European Alzheimer disease consortium. *European Psychiatry*, 20(7), 490-496.
- [55] Perugia, G., Díaz Boladeras, M., Barakova, E., Català Mallofré, A., & Rauterberg, M. (2017, March). Social hri for people with dementia: one size fits all? In *Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction* (pp. 257-258). ACM.
- [56] Peters, C., Pelachaud, C., Bevacqua, E., Mancini, M., & Poggi, I. (2005). A model of attention and interest using gaze behavior. In *International Workshop on Intelligent Virtual Agents* (pp. 229-240). Berlin, Berlin: Springer.
- [57] Nakano, Y. I., & Ishii, R. (2010). Estimating user's engagement from eye-gaze behaviors in human-agent conversations. In *Proceedings of the 15th International Conference on Intelligent User Interfaces* (pp. 139-148). ACM.
- [58] Inoue, K., Lala, D., Nakamura, S., Takanashi, K., & Kawahara, T. (2016). Annotation and analysis of listener's engagement based on multi-modal behaviors. In *Proceedings of the Workshop on Multimodal Analyses enabling Artificial Agents in Human-Machine Interaction* (pp. 25-32). ACM.
- [59] Ekman, P., & Rosenberg, E. L. (Eds.) (1997). *What the face reveals: Basic and applied studies of spontaneous expression using the Facial Action Coding System (FACS)*. New York, New York: Oxford University Press.
- [60] Jaques, N., McDuff, D., Kim, Y. L., & Picard, R. (2016). Understanding and predicting bonding in conversations using thin slices of facial expressions and body language. In *International Conference on Intelligent Virtual Agents* (pp. 64-74). Springer.
- [61] Monkaresi, H., Bosch, N., Calvo, R. A., & D'Mello, S. K. (2017). Automated detection of engagement using video-based estimation of facial expressions and heart rate. *IEEE Transactions on Affective Computing*, 8(1), 15-28.
- [62] Mota, S., & Picard, R. W. (2003). Automated posture analysis for detecting learner's interest level. In *2003 Conference on Computer Vision and Pattern Recognition Workshop (CVPRW'03)* (Vol. 5, pp. 49-49). IEEE.
- [63] Sanghvi, J., Castellano, G., Leite, I., Pereira, A., McOwan, P. W., & Paiva, A. (2011). Automatic analysis of affective postures and body motion to detect engagement with a game companion. In *Proceedings of the 6th International Conference on Human-Robot Interaction (HRI)* (pp. 305-312). ACM/IEEE.
- [64] Ge, B., Park, H. W., & Howard, A. M. (2016). Identifying engagement from joint kinematics data for robot therapy prompt interventions for children with autism spectrum disorder. In *International Conference on Social Robotics* (pp. 531-540). Springer.
- [65] Perugia, G., Díaz-Boladeras, M. D., Català-Mallofré, A., Rauterberg, M., & Barakova, E. (2017, July). Modelling engagement in dementia through behaviour. Contribution for socially interactive robotics. In *2017 International Conference on Rehabilitation Robotics (ICORR)* (pp. 1112-1117). IEEE.
- [66] David, R., Mulin, E., Friedman, L., Le Duff, F., Cygankiewicz, E., Deschaux, O., Garcia, R., Yesavage, J. A., Philip, H. R., & Zeitzer, J. M. (2012). Decreased daytime motor activity associated with apathy in Alzheimer disease: an actigraphic study. *The American Journal of Geriatric Psychiatry*, 20(9), 806-814.
- [67] David, R., Rivet, A., Robert, P. H., Mailland, V., Friedman, L., Zeitzer, J. M., & Yesavage, J. (2010). Ambulatory actigraphy correlates with apathy in mild Alzheimer's disease. *Dementia*, 9(4), 509-516.
- [68] Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6), 1161-1178.
- [69] Andreassi, J. L. (2010). *Psychophysiology: Human behavior and physiological response*. New York, New York: Psychology Press.
- [70] Shukla, J., Barreda, M., Oliver, J., Nandi, G. C., & Puig, D. (2019). Feature Extraction and Selection for Emotion Recognition from Electrodermal Activity. *IEEE Transactions on Affective Computing*.
- [71] van der Zwaag, M. D., Janssen, J. H., & Westerink, J. H. (2013). Directing physiology and mood through music: Validation of an affective music player. *IEEE Transactions on Affective Computing*, 4(1), 57-68.
- [72] Ravaja, N., Turpeinen, M., Saari, T., Puttonen, S., & Keltikangas-Järvinen, L. (2008). The psychophysiology of James Bond: Phasic emotional responses to violent video game events. *Emotion*, 8(1), 114-120.
- [73] Bradley, M. M., Miccoli, L., Escrig, M. A., & Lang, P. J. (2008). The pupil

as a measure of emotional arousal and autonomic activation. *Psychophysiology*, 45(4), 602-607.

[74] Taelman, J., Vandeput, S., Spaepen, A., & Van Huffel, S. (2009). Influence of mental stress on heart rate and heart rate variability. In *4th European conference of the international federation for medical and biological engineering* (pp. 1366-1369). Springer.

[75] Nacke, L. E., Grimshaw, M. N., & Lindley, C. A. (2010). More than a feeling: Measurement of sonic user experience and psychophysiology in a first-person shooter game. *Interacting with Computers*, 22(5), 336-343.

[76] Giblin, L. B., De Leon, L., Smith, L. M., Szynda, T., & Lal, S. (2013). Heart rate variability, blood pressure and cognitive function: Assessing age effects. *Journal of Green Engineering*, 3, 347-361.

[77] Treusch, Y., Page, J., van der Luitj, C., Beciri, M., Benitez, R., Stammler, M., & Marcar, V. L. (2015). Emotional Reaction in Nursing Home Residents with Dementia-associated Apathy: A pilot study. *Geriatric Mental Health Care*, 3(1), 1-6.

[78] Wada, K., Shibata, T., Musha, T., & Kimura, S. (2005). Effects of robot therapy for demented patients evaluated by EEG. In *IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005 (IROS)* (pp. 1552-1557). IEEE.

[79] Wada, K., & Shibata, T. (2008). Social and Physiological Influences of Robot Therapy in a Care House. *Interaction Studies*, 9(2), 258-276.

[80] Kawaguchi, Y., Wada, K., Okamoto, M., Tsujii, T., Shibata, T., & Sakatani, K. (2012). Investigation of brain activity after interaction with seal robot measured by fNIRS. In *21st IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)* (pp. 571-576). IEEE.

[81] Tiberio, L., Cesta, A., Cortellessa, G., Padua, L., & Pellegrino, A. R. (2012). Assessing Affective Response of Older Users to a Telepresence Robot Using a Combination of Psychophysiological Measures. In *21st IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. (pp. 833-838). IEEE.

[82] Vinyoles Bargalló, E., Vila Domènech, J., Argimon Pallàs, J., Espinàs Boquet, J., Abos Pueyo, T., & Limón Ramírez, E. (2002). Concordancia entre el Mini-Examen Cognoscitivo y el Mini-Mental State Examination en el cribado del déficit cognitivo. *Atención Primaria*, 30(1), 5-13.

[83] Folstein, M. F., Robins, L. N., & Helzer, J. E. (1983). The mini-mental state examination. *Archives of general psychiatry*, 40(7), 812-812.

[84] Cummings, J., Mega, M., Gray, K., Rosenberg-Thompson, S., Carusi, D., & Gornbein, J. (1994). The Neuropsychiatric Inventory: Comprehensive assessment of psychopathology in dementia. *Neurology*, 44(12), 2308-2308.

[85] Reisberg, B., Ferris, S., De Leon, M., & Crook, T. (1982). The Global Deterioration Scale for assessment of primary degenerative dementia. *American Journal of Psychiatry*, 139(9), 1136-1139.

[86] Wu, Y., Fassert, C., & Rigaud, A. (2012). Designing robots for the elderly: Appearance issue and beyond. *Archives of Gerontology and Geriatrics*, 54(1), 121-126.

[87] Braithwaite, J. J., Watson, D. G., Jones, R., & Rowe, M. (2013). A guide for analysing electrodermal activity (EDA) & skin conductance responses (SCRs) for psychological experiments. *Psychophysiology*, 49(1), 1017-1034.

[88] Leite, I., Henriques, R., Martinho, C., & Paiva, A. (2013). Sensors in the wild: Exploring electrodermal activity in child-robot interaction. In *Proceedings of the 8th ACM/IEEE international conference on Human-Robot Interaction (HRI)* (pp. 41-48). ACM/IEEE.

[89] Schafer, J. L. (1997). *Analysis of incomplete multivariate data*. New York, New York: CRC Press.

[90] Kang, H. (2013). The prevention and handling of the missing data. *Korean Journal of Anesthesiology*, 64(5), 402-406.

[91] Schumacker, R., & Lomax, R. (2016). *A beginner's guide to structural equation modeling*. New York, New York: Routledge.

[92] Rudovic, O., Lee, J., Dai, M., Schuller, B., & Picard, R. W. (2018). Personalized machine learning for robot perception of affect and engagement in autism therapy. *Science Robotics*, 3, 19.



Dr. Giulia Perugia received a BA in Literature and Linguistics (RomaTre), a M.Sc. in Cognitive Science (University of Siena), and a double degree Ph.D. in Assistive Technologies from UPC and TU/e. Currently, she is a postdoctoral researcher at Uppsala Social Robotics Lab (Uppsala University). Her research interest lies at the intersection of HRI, Social Psychology, Social Robotics, and Multimodal behavior. In 2017, she was awarded the Distinguished Interdisciplinary Research Award by the Robotic Society of Japan (RSJ) and the Korean Robotics Society (KROS).



Prof. Dr. Marta Díaz-Boladeras received a B.Sc. and M.Sc. degree in Psychology from the University of Barcelona (UB), a M.Sc. in Occupational Risk Prevention, Ergonomics and Applied Psycho-Sociology from UPC, a Ph.D. in Business Administration from the Department of Management of UPC, and a Ph.D. in Psychology from UB. She directs the IBuX-Lab, a research lab on interaction and usability. Her research interests are social human-robot interaction and ICT systems design for health and well-being. Her current research focuses on the application of Social Psychology and Ethology models and methods to long-term Human-Robot Interaction.



Prof. Dr. Andreu Català Mallofré has a B.Sc. and M.Sc. in Physics from UB and a Ph.D. in Physics from UPC. He is Professor in the Department of Automatic Control at UPC and Director of the Research Centre for Dependency Care and Autonomous Living (CETpD). Between 200-2006, he was Dean of the Engineering School of Vilanova i la Geltrú. His research interests include Assistive Technologies, Artificial Intelligence, Social Robotics, Wearable and Intelligent Sensors. He coordinated several international and national research projects, among which E-NOFALLS (2013-16)



Dr. Emilia Barakova is Assistant Professor of Socially Intelligent Systems at Eindhoven University of Technology (TU/e) where she leads the Social Robotics Lab and the Physical and Social Rehabilitation educational squad. Barakova expertise regards embodied social interaction, social, cognitive and brain-inspired robotics, modeling expressiveness of movement, and design technologies for people with special needs. She served as intermediate director of the German-Japanese Research Lab in Japan and worked for 4 years at RIKEN Brain Science Institute in Japan.



Prof. Dr Matthias Rauterberg received a B.A. in Philosophy, a B.Sc. and M.Sc. in Psychology, a B.Sc. and M.Sc. in Computer Science, and a Ph.D. in Computer Science/Mathematics. He is full professor of 'Interactive System Design' at Eindhoven University of Technology (TU/e). He was visiting professor at Kwansai Gakuin University (Japan) in 2004-2007 and guest professor at the School of Design of Jiangnan University (China) and East China University of Science and Technology, respectively in 2011-2015 and 2013-2016. He received the German GI-HCI Award for the best Ph.D. in 1997 and the Swiss Technology Award for the BUILD-IT system in 1998. In 2007, he received the Silver Core Award from IFIP.