D3.4.1
Emotion and Psychosocial Analytics

Work package	**WP3 Multimodal Analytics and Assessment**
Task	**T3.4 Emotion and Psychosocial Analytics**
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Project PLAYTIME

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Contents

1 Executive Summary

Emotion plays a major role in the frame of process- or outcome-focused motivation (Toure-Tillery & Fishbach, 2014). Emotion-oriented care can be more effective than standard care with regard to positive emotion in nursing homes residents with mild to moderate dementia (Finnema, et al., 2005). Emotion-oriented care approaches are in principle known to offer the opportunity to tailor the care to the individual needs of dementing elderly. PLAYTIME applies a serious game approach that will investigate the relation of users emotions to cognitive performance.

Engagement is an essential element of the serious game player experience and the concept is described extensively in the literature. Empirical studies have identified a range of components associated with engagement and the desire to continue playing to guide game design (Schoenau-Fog, 2011).

The present deliverable relates to emotion measurements and contextual relations in the framework of SERES (MBY). The SERES platform of MBY currently reflects the Objectives, Activity, Accomplishment and Affect (OA3) framework for player engagement stipulated in (Schoenau-Fog, 2011) and will be adapted to the requirements in PLAYTIME by MBY. Further insights into the PLAYTIME intervention suite of games will be gained by relating emotion analytics to the amicasa training as well as to the MIRA games.

Furthermore, it is described how PLAYTIME will employ emotion analytics by means of state-of-the-art visual and/or psychophysiological emotion estimation methods to provide a basis for further integrated analytics.

2 Introduction

This deliverable intends to explore the influence of emotions on motivation in the context of playful training and serious games for people with dementia (PwD) and their informal caregivers (Cg). Related to this, the deliverable also explores emotional analytics and their use in the assessment of PwD and Cg. Not only could this serve as a method for evaluating emotional status of end users, but it could also serve as an input with which the artificial intelligence components of PLAYTIME recommend training and serious games to the user. This deliverable will also determine how emotions could be evaluated in real-time with diagnostic methodologies applied by PLAYTIME consortium partners such as, gaze analytics, or other psychophysiological methods.

3 PLAYTIME objectives related to emotion

PLAYTIME's ultimate goal is persistent behavior change through engaging people with dementia (PwD) and their informal caregivers (Cg). Accordingly, persuading and motivating users to interact with the game system is vital. In turn, as emotion plays a critical role in mediating outcome-focused motivation, PLAYTIME intends to study emotion and motivation of PwD and Cg and the respective mechanisms through which they impact training outcomes (Toure-Tillery & Fishbach, 2014). Tailoring care to the individual needs of people with dementia (PwD) – an integral component of caring for PwD – can be addressed through various game mechanics (difficulty, agency, control, etc.) but it can also align with the socio-emotional state of the user. This concept will be integrated into the suite of games within PLAYTIME.

Research findings have demonstrated that emotion can induce positive increases in executive control, an important cognitive process that inexorably worsens in individuals with Alzheimer's disease (Kanske & Kotz, 2011).

Therefore, PLAYTIME aims to leverage the positive influence of emotion and motivation to strengthen executive performance and enhance psychosocial experience by engaging PwD. These are relevant factors that could, in turn, result in a material impact on the quality of life of PwD and their informal Cg. As this has not been studied to date in the context of serious games, this will be the integral research focus in PLAYTIME. In particular, the consortium will evaluate the mechanisms through which PwD improve executive function and well-being. Moreover, the influence of mood on motivation and training engagement will also be studied.

3.1 Emotion in a socio-emotional context

3.1.1 Psychosocial factors & emotion

MindBytes has created an innovative interactive serious game platform that has been used to develop serious medical games. The system focuses on promoting behavioral changes by simulating the impact of user decisions on emotional and psychosocial factors in a game setting, and has been shown to be efficacious at persuading players through a pilot trial. As MindBytes has mapped the key psychosocial factors in the context of dementia, its serious game platform allows for the collection of a user's starting psychosocial factors and the status over time as a result of user behaviors. Psychosocial factors such as social relationships, self-efficacy, self-esteem, etc. are influenced by emotions and, in turn, influence emotions. Therefore, MindBytes' serious game platform models emotions and psychosocial factors and inter-relationships between the two to provide feedback to users on the consequences of their behaviors.

3.1.2 Contextual emotion analytics

As described previously, emotion is a relevant factor to consider when maximizing user motivation, as is the objective in PLAYTIME. Moreover, emotion is even more important in the context of dementia due to its influence on cognition, specifically executive function, and behavior. As these outcomes are chief drivers of a PwD's quality of life (QoL), emotions are also an important factor impacting not only a PwD but also a Cg due to the interplay between a PwD QoL and their Cg's QoL. As MindBytes' serious game platform models the impact of user decisions, it maintains an awareness of in-game emotions and psychosocial statuses. Therefore, artificial intelligence components in MindBytes' serious game engine can modify the game environment in real-time to more accurately reflect the evolving emotional and psychosocial statuses. In addition, it could generate game content that will help a user's to improve their emotional status – thereby increasing self-efficacy, which is an important driver of behavior change. This also serves as an approach to tailor content to each user, depending on their emotional and psychosocial status.

3.2 Emotion measurement technology

Emotion plays a central role in the parametrization of human behavior, such as, in the interplay between emotion and cognitive control via the dual competition framework (Pessoa, 2009). Emotion and motivation have an amplifying or inhibiting effect on the performance of human behavior, in particular, in attention driven tasks, and in this sense are intrinsically linked to eye movement analysis.

The capacity to regulate emotion is an important cognitive function for human adaptation, and the regulatory efforts largely determine the impact that some negative emotions will have on our mental health and physical well-being (Ochsner & Gross, 2005). Mental health technologies have recently increasingly emerged from innovations in novel affordances in human-computer interaction (Wadley et al., 2018) as well as in the measurement technologies (Gregg & Tarrier, 2007). Virtual reality has been widely applied in the assessment, understanding, and treatment of mental health disorders (Freeman et al., 2017). However, although neurological disorders can be diagnosed using eye movement analysis (Tseng et al., 2012) - such as, for Alzheimer (Molitor et al., 2015) and ADHS (Kemner et al., 1998) – Virtual Reality and eye tracking has not been integrated for mental health at large.

Emotion plays a major role in the frame of process- or outcome-focused motivation [24] which is an essential parameter in healthcare oriented training processes. Emotion-oriented care can be more effective than standard care with regard to positive emotion in nursing homes residents with mild to moderate dementia (Finnema et al., 2005). Playful and personally unaware emotion measurement are preferred to subjective emotion statements, such as, in Pick-a-Mood (Desmet et al., 2016) or SAM (Morris et al., 1992) since we assume higher potential for credible repetitions.

The presented work therefore attains to start to bridge a gap to make everyday emotion sensing in mental health care possible, in a framework of playful diagnostics.

3.3 Subjective emotion measurement

3.3.1 Off-line questionnaires

Structured questionnaires are commonly used methods to evaluate an individual's emotional status. Additionally, these questionnaires are often applied from a diagnostic perspective to evaluate an individual for presentation with mood or thought disorders. Therefore, a number of validated questionnaires are described in the scientific literature and applied in clinical settings, which are specifically designed for distinct psychopathologies, such as anxiety or depression. In the context of dementia, several questionnaires are available to assess a PwD for depression or anxiety such as the Geriatric Depression Scale, Cornell Scale for Depression, Montgomery-Asberg Depression Rating scale (MADRS), among others (Sheehan, 2012). In certain instances, the same scale can be used to assess the emotional status of a Cg, such as the MADRS. Scales differ in their duration, assessor requirements, and sensitivity. In particular, a number of validated assessments are performed by trained assessors (clinician) whereas others, such as the MADRS-S, are self-reported (Sheehan, 2012).

3.4 Eye tracking based emotion measurement

Measuring human emotion from affective interaction is an important part of computing for mental health applications. In the frame PLAYTIME, the potential of applying non-obtrusive emotion measurements from eye tracking has been investigated by means of a fully immersive, i.e., a Virtual Reality (VR) technology (Paletta & Dini, 2018) that could be applied as well using the Tablet PC.

In (Paletta & Dini, 2018) PLAYTIME contributed to provide a concept and first results of a feasibility study in which affectively weighted imagery of an image database were presented and integrated using discriminative observation, multi-object tracking and video-gaming. Attention preference for affective image classes was measured and relevant correlation with data extracted from a questionnaire on emotional states (MDBF) that would eventually substantiate basic valence classification from eye tracking data was found.

The playful approach using the well-known concentration (pairs) game enables frequent repetition of the measurements in mental health care, therapeutic or pedagogical scenarios (Paletta & Dini, 2018).

Technologies for the measurement of human emotion play an important part in the impact of affective computing in human computer interaction (Picard, 1997; Breazeal, 2009). Computing methods for emotion recognition have emerged from the analysis of a variety of multimodal sensors (Pantic & Rotkrantz, 2003), such as, psychophysiological (Mandryk & Atkins, 2007), EEG (Harmon et. al, 2006), electromyography (Mauss & Robinson, 2009), audio (Schuller & Batliner, 2013) and camera based facial behavior information (Pantic, 2009; Robinson & Kaliouby, 2009).

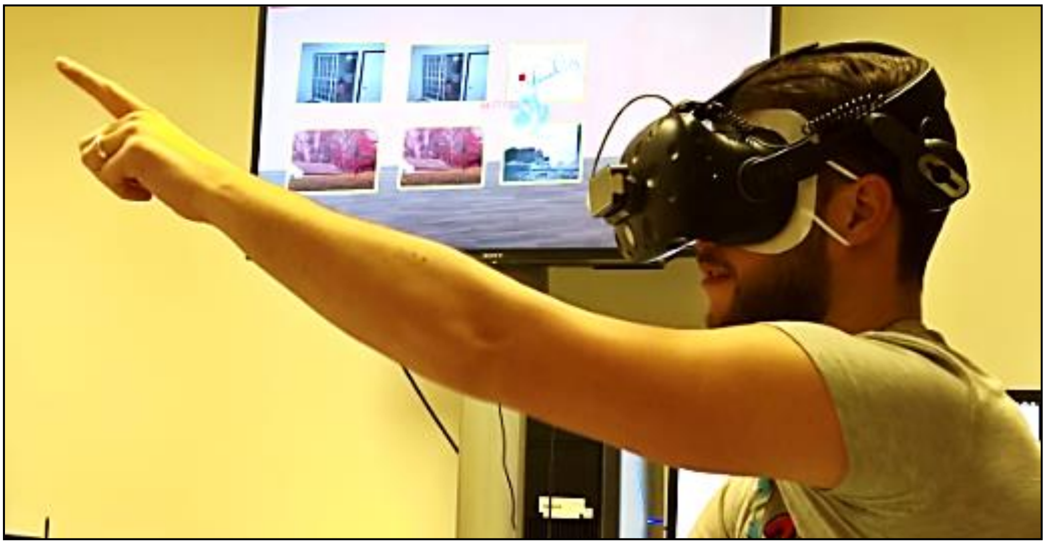

Figure 1. Measurement of emotion using VR technology with built-in eye tracking and analysis of gaze behavior towards selected stimuli of an affective image database (Dan-Glauser & Scherer, 2011). Participants manually select image pairs in a concentration game while gaze (red point on operator display) is tracked.

The presented work refers to emotion measurement exclusively from eye tracking data in Virtual Reality (VR) technology. Eye tracking is a non-invasive technology that gets increasingly ubiquitous. The advantage of VR is the high degree of immersion of users towards artificially created stimuli. Methods involving affective feedback are first designed in VR technology and can be transferred onto other devices, such as, tablet PCs, smart-TV, and smartphone devices.

We propose a concept and first results of a feasibility study in which affectively weighted imagery of the GAPED database 9. (Dan-Glauser & Scherer, 2011) is presented and integrated using discriminative observation, multi-object tracking and video-gaming. We measured attention preference for affective image classes and found relevant correlation with data of the MDBF questionnaire (Hinz et al., 2011) on emotional states that would eventually substantiate basic valence classification only from eye tracking data. A playful approach using the well-known concentration (pairs) game enables frequent repetition of the measurements in mental health care (Sarkany et al., 2015) or pedagogical scenarios.

3.4.1 Theory on emotion and attention

The experimental link between eye tracking and emotion measurement has recently been discovered in the frame of neuropsychological research and affective image databases. (Armstrong & Olatunji, 2012) demonstrated that affective disorders can be precisely measured in eye tracking studies. In particular, participants with depression showed reduced orientation towards and focus on positive stimuli while having longer focus duration on stimuli with dysphoric content (Sears et al., 2010). Research on persons without affective disorders but with sensitive emotional regulation in pre- or post-clinical state are also demonstrating differences in attention based processing of emotional stimuli. These investigations resulted in differences in pupil diameter behavior (Steidmann et al., 2010), visual search Wenzlaff et al., 2001), and selection of positive and negative facial emotions (Joormann & Gotlib, 2007).

The objective of the presented emotion measurement technology is to estimate the emotional state determined by a standardized questionnaire of emotion psychology (Boyle et al., 2015). Positive and negative affect are usually measured with the PANAS-X (Watson & Clark, 1999) to measure momentary emotional state. However, other dimensions, such as, arousal, are not analyzed. Therefore, this work refers to the MDBF questionnaire on emotional states (Hinz et al., 2011) that is capable to determine affective dimensions of valence and arousal Serious games for mental health are seen as the groundwork for assistive technology to maintain and improve mental health (Molitor et al., 2015).

3.4.2 Affective imagery

In the playful emotion measurement technology developed by (Paletta & Dini, 2018), there is one pair of each category, i.e., of (a) positively, (b), neutrally and (c) negatively weighted images, presented at the same time. The user should now memorize the positions of the images since these will be moving in a later stage of the game. The images that are triggering the emotion of users are selected out of the GAPED pool of 130 positive, 111 neutral and 126 (humans) as well as 131 (animals) negative images. There is no consideration about the individual weighting of the imagery. It is important to determine that positions within the sextet are randomized so that no stimulus class is preferred by position. In particular, over a sufficiently extended sequence of games, stimuli are globally assumed to be uniformly distributed in value and position and sum up to zero triggering of specific emotions. Therefore, only the specific reaction of users would enable to determine the specific emotion state during eye tracking.

3.4.3 Playful emotion measurement

The emotion measurement technology is implemented using the well-known concentration (pairs) game. The objective of a game is to offer the opportunity to users to enjoy the game and in this sense gain emotional data more frequently for investigation.

Pairs game for emotion measurement

The game consists of the following stages, see

Figure 2:

- Initialization by forcing a referenced focus of attention in the center of the display using a cross-hair symbol (3 seconds).
- Presentation of 3 pairs of different affective images of GAPED database (Dan-Glauser & Scherer, 2011) (10 seconds). The user should memorize positions of images since these will be moving in a later stage of the game.
- Flipping of the images and the backside of cards with unified appearance is shown. The user has to memorize by heart the position of the images.

- Synchronous motion of the cards to other positions that were randomly selected, via 3 separated motions, each with a duration of 3 seconds. The user has to track the positions of memorized images along several motion stages.
- Interactive selection of image pairs using an intuitive interaction tool, i.e., the user's own hands. By finger-tipping on the cards in virtual Space (Figure 5), cards are flipping back and the image is displayed. If the pair of flipped images does not match the user needs more attempts to flip the complete card set back. The user in this way can perform several errors.

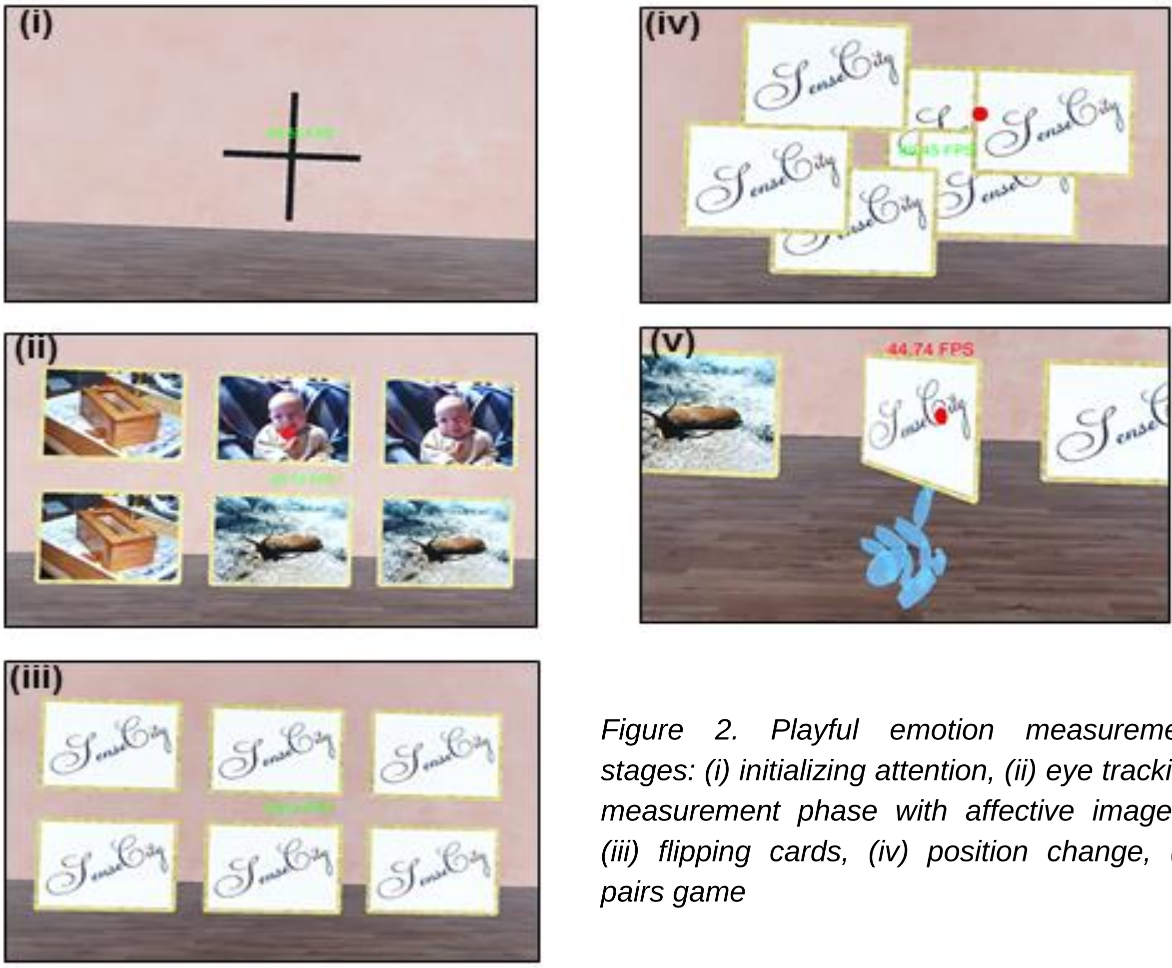

Figure 2. Playful emotion measurement stages: (i) initializing attention, (ii) eye tracking measurement phase with affective imagery, (iii) flipping cards, (iv) position change, (v) pairs game

Figure 3: Hand gesture (Leap Motion) for the selection of affectively weighted image 'cards'.

Figure 4: For the VR study a HTC Vive head-mounted device with built-in eye tracking from Tobii and Leap Motion sensor was used.

Figure 5: Hand gesture for interaction, such as, for progressing in the calibration procedure.

3.5 PLAYTIME component for instant emotion analytics

3.5.1 The Affective Slider (AS) measurement technology

Self-assessment methods are broadly employed in emotion research for the collection of subjective affective ratings. By leveraging on state-of-the-art user interfaces and meta-communicative pictorial representations, (Betella & Verschure, 2016) developed the Affective Slider (AS), a digital self-reporting tool composed of two slider controls for the quick assessment of pleasure and arousal. The AS has two added advantages over comparable implementations: the AS does not require written instructions and it can be easily reproduced in latest-generation digital devices, including smartphones and tablets.

Figure 6 presents the appearance of the "Affective Slider" (AS) that is intentionally displayed using a neutral chromatic palette to avoid bias in ratings due to the emotional connotation of colors.

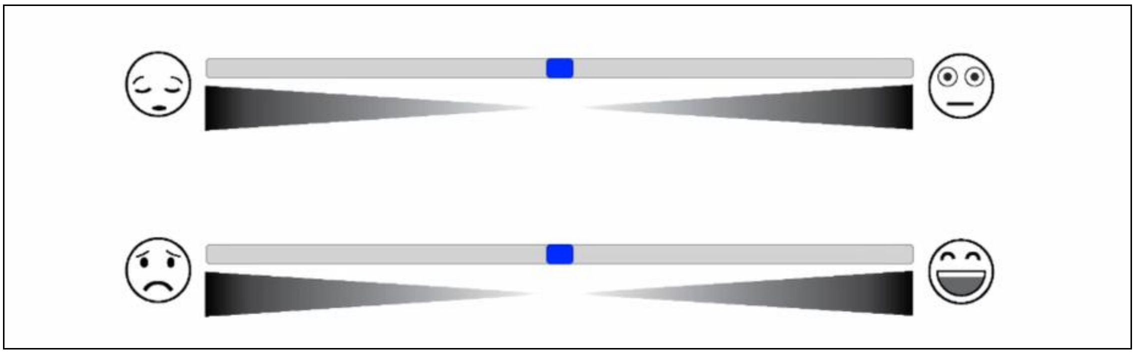

Figure 6. The "Affective Slider" (AS) is a digital self-reporting tool composed of two sliders that measure arousal (top) and pleasure (bottom) on a continuous scale. The AS does not require written instructions and it is intentionally displayed using a neutral chromatic palette to avoid bias in ratings due to the emotional connotation of colors.

3.5.2 Pick-a-mood (PAM) measurement technology

'Pick-A-Mood' (PAM; Desmet et al., 2012) is a cartoon-based pictorial instrument for reporting and expressing moods. The use of cartoon characters enables people to unambiguously and visually express or report their mood in a rich and easy-to-use way. PAM consists of three characters that each express eight different mood states, representing four main mood categories: energized-pleasant (excited and cheerful), energized-unpleasant (irritated and tense), calm-pleasant (relaxed and calm), and calm-unpleasant (bored and sad).

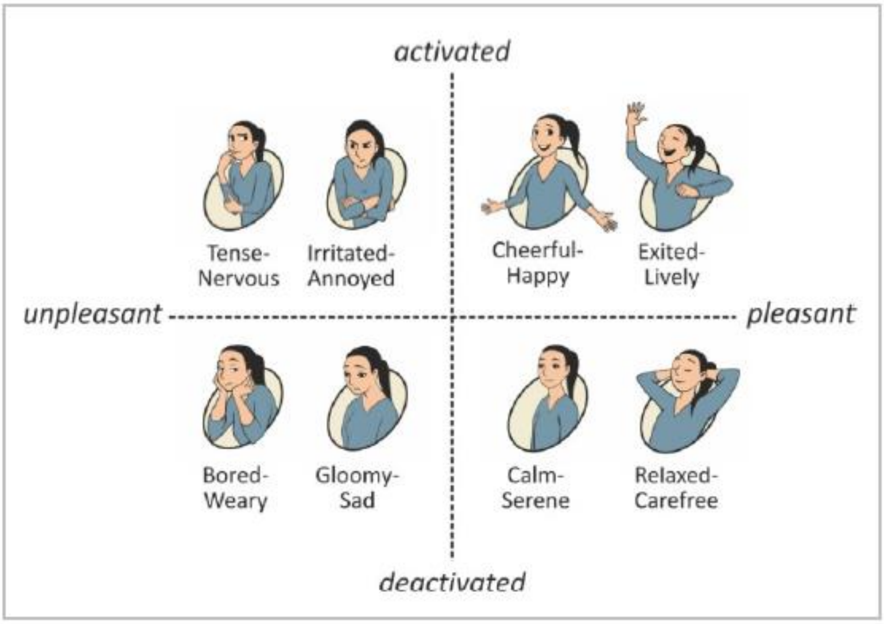

Figure 7. Pick-a-mood (PAM) technology used in situations in which people have little time or motivation to report their moods.

The added value of PAM compared to existing instruments, is that it requires little time and effort of the respondents, which makes it suitable for design research applications, which are often **used in situations** in which **people have little time or motivation to report their moods**. Mood is defined, a brief review of existing instruments is provided, and the development and validation of PAM is reported. It is argued and shown in (Desmet et al., 2012) that PAM can be used both as a tool for measurement (i.e. to enable researchers to measure the moods of their respondents) and as a tool for communication (i.e. to enable people to communicate their mood in social interactions).

PAM was tested with a general population (Desmet. 2016). In the validation study, 191 people participated, including 31 different nationalities, with people from various countries in Europe, Asia, Australia, South-America, Canada, and the Middle-East. Age ranged between 13 and 76 (mean = 34,9; SD = 13,0), and 47% were female. PAM was not tested with children younger than 13 years old, nor with target groups who have difficulties with recognizing emotional expressions (e.g. due to medical reasons). For application with these participants, it is advised to test the applicability of the characters with a pilot study.

The advantage of using PAM is also that it does not need elaborated interaction tools to be implemented but rather it is used as a button-like selection of a specific mood.

4 Contextual emotion analytics

4.1 SERES: socio-emotional dimension measurement

MBY's SERES Dementia is a socio-emotional serious game, which playfully simulates realistic situations and, in turn, requires decision-making by end users. In the context of PLAYTIME, SERES presents end users with situations related to cognitive, functional, or behavioural challenges, which is consistent with the main domains of impairment in dementia (NICE, 2007). Users are presented with both quantitative and qualitative feedback based on the decision choice that they make. The quantitative feedback is presented as the change in the value of key outcomes (caregiver quality of life, person with dementia quality of life, and societal integration). These outcomes are calculated based on the impact of decision choices on underlying psychosocial determinants, which have been defined through literature review and expert input. In practice, this means that the SERES engine has an awareness of the change in psychosocial determinants (and resulting outcomes) after every user decision. As one can imagine, user decisions result in the generation of robust amounts of data and therefore, MBY has been researching the use of artificial intelligence to understand this data and ensure seamless game flow.

4.1.1 Baseline

Standardized questionnaires, as described in section 3.3.1, can be used to collect a user's baseline state with respect to psychosocial determinants because the determinants applied in SERES Dementia are components of the gold standard measures used in dementia research and care (MADRS, CDS, NPI, etc.). Therefore, the SERES artificial intelligence engine will have a baseline state of both clinical (domains of impairment) and psychosocial factors (determinants), including emotions. These states can be used to select the most applicable domains (and situations therein) from a library of scenarios that are most relevant to the user (e.g. require most support or training). This personalization is intended to maximize engagement and motivation as the scenarios will be tailored to the needs of the individual user. This work has not been integrated into the SERES serious games that will be evaluated within the FT2 study but will be incorporated into PLAYTIME afterwards.

4.1.2 During play

The selection of a decision by the user results in changes to psychosocial determinants, which are calculated by the SERES artificial intelligence engine. This means that the AI engine has a log of the changes in psychosocial and emotional states from baseline. This information will be used to further personalize the scenarios and qualitative feedback to the end user. This work has not been integrated into the SERES serious games that will be evaluated within the FT2 study but will be incorporated into PLAYTIME afterwards.

Emotion collected from other PLAYTIME modules and stored in the central PLAYTIME database could also be used to adapt content in the SERES serious game. For example, if users interact with other modules first in a single session, the data collected on emotion could serve as input to the content. If users are in a negative emotional state, certain scenarios could be avoided or others emphasized – even *easier* (clinically less complex) situations could be presented.

4.1.3 After play

For the FT2 study, MBY has also added an AS at the end of each module with the purpose of collecting data on the emotional state of the user. Although this can be considered instant emotional data, as described in section 3.5, the emotion is being collected immediately after a cognitive task (simulation of realistic decision-making). These emotions could also be compared to baseline states to form an understanding of how user emotions have changed after interaction with specific serious game content. Moreover, it’s conceivable that there is a link between emotional state and serious game content (e.g. domain of impairment). MBY will review data from the FT2 study with the intention of identifying links between emotion and choice decisions and content domains. In addition, MBY will analyse the FT2 data to determine if there is a relationship between psychosocial determinants and emotion in the context of the socio-emotional serious game. All data can be sent to the central PLAYTIME database and therefore could also serve as input to tailor content of other modules in the PLAYTIME suite.

4.2 MIRA component for contextual emotion analytics

4.2.1 Emotion and performance (MIRA)

In the MIRA component we will collect data about individual emotion using the Affective Slider (AS) technology (Section 3.5.1). The reason to prefer this technology is to receive a gradual and potentially more authentic input about a current mood then it would be for a PAM request. This would be due to the fact that some persons hesitate to decide for a discrete representation of a mood but rather like to provide input through an analogue type medium as in the case of the slider based selection process.

The integration of AS based emotion measurements into the control flow of MIRA is described in more detail in Deliverable D3.3.1. Basically, it is planned to perform one measurement before as well as one additional measurement after the MIRA session had been completed. These data will be investigated in more detail with respect to the following purposes:

- Does the MIRA attentive game contribute to an increase of the emotional status ?
- How do the scores that are obtained from the attention gameplay - that indicate well working executive functions - correlate to the respective emotional data.
- Psychology predicts slightly low emotional values should have a consequence in better cognitive performance while high emotional values would cause probably slightly lower cognitive performance. Please refer to Deliverable D3.1.1 and D3.1.2 for more insight into this

The analysis derived from these research questions will feed into health care oriented assessment (Deliverable D3.5.1) as well as into the recommender (Deliverable D4.5.1).

4.2.2 Emotion and performance (amicasa)

In the current version of the amicasa component, we will collect data about individual emotion using the “Pick-a-mood” (PAM) technology (Section 3.5.2). The reason to prefer this technology is to continue with a pictorial representation in order not to annoy users when interacting or a long time with the Tablet PC, and that it does not need an elaborated software interface toolbox and therefore works well with a vast majority of graphical user interfaces.

The application of emotion measurements within the amicasa sequence of training units (see Deliverable D4.1.1) will enable to investigate, in the line of research described in Sec. 4.2.1, the relations between emotion and performance, in particular, considering the dementia prone mental processes. Furthermore, the data collection will enable to find more or less liked parts of the amicasa session components and from this the recommender can be instructed to react likewise and improve overall performance in an adaptive way.

5 Conclusions and Outlook

This deliverable introduced into the activities and plans for future developments of Task 3.4 “Emotion & Psychosocial Analytics“ of work package WP3 “Motivational Analytics and Assessment”. This deliverable is the first in a line of three in the frame of Task 3.4 and is therefore defined to initiate the process of a “living document”.

The work of Task 3.4 is documented in this deliverable and in this sense presented results on state-of-the-art of emotion measurement technologies, in particular, with respect to the application to MIRA attention games as well as to amicasa and SERES.

The next deliverable, D3.4.2, will include final adjustments that will be jointly agreed to get into the PLAYTIME prototype for the second field trials.

6 Abbreviations

Table 1. *Abbreviations.*

Abbreviation	Description
AS	Affective Slider technology
PAM	Pick-a-mood technology
PwD	Person with dementia

7 Bibliography

(**Armstrong & Olatunji, 2012**) Armstrong, T., Olatunji, B.O. (2012). Eye tracking of attention in the affective disorders: A meta-analytic review and synthesis, Clinical Psychology Review.

(**Betella & Verschure, 2016**) Betella A, Verschure (2016) The Affective Slider: A Digital Self-Assessment Scale for the Measurement of Human Emotions. PLoS ONE 11 (2): e0148037. doi:10.1371/journal.pone.0148037.

(**Boyle et al., 2015**) Boyle, G.J., Helmes, E., Matthews, G., and Carroll, E.I. (2015). Measures of Affect Dimensions, in Measures of Personality and Social Psychological Constructs.

(**Breazeal, 2009**) Breazeal, C. (2009). The role of expressive behavior for robots that learn from people. Phil. Trans. R. Soc. B.

(**Dan-Glauser & Scherer, 2011**) Dan-Glauser, E.S., and Scherer, K. (2011). The Geneva affective picture database (GAPED): a new 730-picture database focusing on valence ad normative significance, Behav. Res., 43:468-477, 2011.

(**Desmet et al., 2012**) Desmet, P.M.A., Vastenburg, M.H., Van Bel, D., & Romero, N. (2012) Proceedings of 8th International Design and Emotion Conference London 2012 Central Saint Martins College of Art & Design, 11-14 September 2012.

(**Desmet et al., 2016**) Desmet, P. M. A. et al. (2016). Mood Measurement with Pick-A-Mood; Review of current methods and design of a pictorial self-report scale. J. Design Research.

(**Desmet. 2016**) Desmet, P.M.A., Vastenburg, M.H., & Romero, N. (2016). Pick-A-Mood Manual; Pictorial self-report scale for measuring mood states. Delft: Delft University of Technology.

(**Finnema et al., 2005**) Finnema, E., Dröes, R.-M., Ettema, T.P., and van Tilburg, W. (2005). The effect of integrated emotion-oriented care versus usual care on elderly persons with dementia in the nursing home and on nursing assistants: A randomized clinical trial. Intl. J. Geriatric Psychiatry.

(**Freeman et al., 2017**) Freeman, D. Reeve, S., Robinson, A., Ehlers, A., Clark, D., Spanlang, B., and Slater, M. (2017). Virtual reality in the assessment, understanding, and treatment of mental health disorders. Psychol Med.

(**Gregg & Tarrier, 2007**) Gregg, L., and Tarrier, N. (2007). Virtual reality in mental health. A review of the literature, Social Psychiatry and Psychiatric Epidemiology, 42(5):343-54.

(**Harmon et. Al, 2006**) Harmon-Jones E, Lueck L, Fearn M, Harmon-Jones, C. (2006). The effect of personal relevance and approach related action expectation on relative left frontal cortical activity. Psychological Science.17(5):434–440.

(**Hinz et al., 2011**) Hinz, A. et al. (2011). Norms of the multidimensional mood questionnaire MDBF, Psychother Psych Med, 62.

(**Joormann & Gotlib, 2007**) Joormann, J. & Gotlib, I. (2007). Selective attention to emotional faces following recovery from depression. Journal of Abnormal Psychology, 116(1), 80–85.

(**Kanske & Kotz, 2011**) P Kanske, SA Kotz. Human brain mapping 32 (2), 198-208, 2011

(**Kemner et al., 1998**) Kemner C., Verbaten M. N., Cuperus J. M., Camfferman G., Engeland H. (1998). Abnormal Saccadic Eye Movements in Autistic Children, Journal of Autism and Developmental Disorders, 28(1), p. 61-67.

(**Lithari, C. et al., 2010**) Lithari, C. et al. (2010). Are females more responsive to emotional stimuli? A neurophysiological study across arousal and valence dimensions. Brain topography.

(**Mandryk & Atkins, 2007**) Mandryk, R., Atkins, M. (2007). A fuzzy physiological approach for continuously modeling emotion during interaction with play technologies. International Journal of Human-Computer Studies. 65, 329–347.

(**Mauss & Robinson, 2009**) Mauss, I. B., and Robinson, M. D. (2009). Measures of emotion: A review. Cognition and Emotion, 23.

(**Molitor et al., 2015**) Molitor,R.J., Ko,P.C., Ally, B.A. (2015). Eye Movements in Alzheimer’s Disease, J Alzheimers Dis.

(**Morris et al., 1992**) Morris, J. D., Bradley, M., Lang, J. and Waine, C. (1992). Assessing affective reactions to advertisements with (SAM) the Self-Assessment Manikin. Univ. Florida.

(**NICE, 2007**) Dementia: A NICE-SCIE Guideline on supporting people with dementia and their carers in health and social care. London, UK.

(**Ochsner & Gross, 2005**) Ochsner K N, Gross J J. (2005). The cognitive control of emotion. Trends Cogn Sci, 9: 242—249.

(**Ochsner & Gross, 2005**) Ochsner K N, Gross J J. (2005). The cognitive control of emotion. Trends Cogn Sci, 9: 242—249.

(**Pantic & Rotkrantz, 2003**) Pantic, M., and Rothkrantz, L.J.M. (2003). Toward an affect-sensitive multimodal Human-Computer Interaction. Proc. of the IEEE, vol. 91(9), 1370-1390.

(**Pantic, 2009**) Pantic, M. (2009). Machine analysis of facial behavior: naturalistic and dynamic behaviour. Phil. Trans. R. Soc. B.

(**Pessoa, 2009**) Pessoa, L. (2009). How do emotion and motivation direct executive control? Trends Cogn Sci.

(**Picard, 1997**) Picard, R. W. (1997). Affective computing. MIT Press.

(**Pylyshyn & Storm, 1988**) Pylyshyn, Z.W. and Storm, R.W. (1988). Tracking multiple independent targets: evidence for a parallel tracking mechanism. Spatial Vision, 3(3): p. 1-19.

(**Robinson & Kaliouby, 2009**) Robinson, P. and el Kaliouby, R. (2009), Computation of Emotion in Man and Machines. Phil. T. Royal Soc.

(**Sarkany et al., 2015**) Sarkany, A., Töser, Z., Verö, A., Lörincz, A., Toyama, T., Toois, E.N., Sonntag. D. (2015). Maintain and Improve Mental Health by Smart Virtual Reality Serious Games.

(**Schoenau-Fog, 2011**) Schoenau-Fog, H. (2011, September). The player engagement process: An exploration of continuation desire in digital games. Paper presented at Think Design Play: The fifth international conference of the Digital Games Research Association (DiGRA), Utrecht, Netherlands.

(**Schuller & Batliner, 2013**) Schuller, B. and Batliner, A. (2013). Computational Paralinguistics: Emotion, Affect and Personality in Speech and Language Processing. Wiley, November 2013.

(**Sears et al., 2010**) Sears, C. R., and Thomas, C.L., LeHuquet, J.M., and Johnson, J.C.S. (2010) Attentional bias in dysphoria: An eye-tracking study of the allocation and disengagement of attention, Cognition and Emotion.

(**Serino et al., 2015**) Serino, S., Matic, A., Giakoumis, D., Lopez, G. , and Cipresso, P. (2015), eds., Pervas. Comp. Parad. M.Health.

(**Steidmann et al., 2010**) Steidmann, D., Ingram, R. E., & Siegle, G. J. (2010). Pupil response to negative emotional information in individuals at risk for depression. Cognition and Emotion.

(**Toure-Tillery & Fishbach, 2014**) Toure-Tillery & Fishbach (2014). How to Measure Motivation: A Guide for the Experimental Social Psychologist. Social and Personality Psychology Compass.

(**Tseng et al., 2012**) Tseng P. H., Cameron I. G. M., Pari G., Reynolds J. N., Munoz D. P., Itti L. (2012). High-throughput classification of clinical populations from natural viewing eye movements, Journal of Neurology.

(**Wadley et al., 2018**) G. Wadley, R.A. Calvo, J. Torous, M. Czerwinksi (2018). 3rd Symposium on Computing and Mental Health: Understanding, Engaging, and Delighting Users. in Proceedings of the 2018 CHI Conference Extended Abstracts on Human Factors in Computing Systems.

(**Watson & Clark, 1999**) Watson, D., & Clark, L. A. (1999). The PANAS-X: Manual for the Positive and Negative Affect Schedule Expanded Form. Cedar Rapids, IA:University of Iowa.

(**Wenzlaff et al., 2001**) Wenzlaff, R. M., Rude, S. S., Taylor, C. J., Stultz, C. H., & Sweatt, R. A. (2001). Beneath the veil of thought suppression: Attentional bias and depression risk. Cognition and Emotion, 15, 435–452.