Special Issue “Technology for Mental Health”

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1. Introduction

There is an increasing number of research initiatives that utilize modern technology in order to support patients in maintaining or regaining a healthy mental state. Advanced technological solutions have been exploited for treating depression, anxiety disorders, and for coping with stress. This is of utmost importance to provide people with higher quality of life and also to shift a part of monitoring tasks from therapists and caregivers to unobtrusive technological systems. In addition they can provide the patient with self-guidance possibilities that enable a more easily accessible form of treatment. Efforts have started with Internet-based self-help therapies and have continued with an increasing use of ubiquitous computing for providing effective solutions for maintaining and improving mental health. However, technology is always moving towards further miniaturization and increased computational power, constantly challenging researchers to creatively exploit new potentials in order to mitigate the prevalence of mental disorders which affect around a quarter of all people at some point in their life. Therefore, there is a significant need to have platforms for exchanging the latest achievements and motivating further advances in this research area.

This Special Issue on “Technology for Mental Health” contains four significant contributions provided by researchers from both psychological and technological fields that share the same interest of improving both the treatment of mental disorders and wellbeing of healthy individuals.

Wolters et al. describe a promising approach for managing data in the treatment of depression. The system consists of the three components, namely Personal Monitoring System, Virtual agent with an avatar interface, and Decision Support System. The authors describe how the complex data is managed and also they discuss related ethical issues. The proposed solution is interoperable with other applications such as Electronic Health Records.

Cavanagh and Millings discuss the issues related to the user engagement in CCBT (Computerized Cognitive Behavioral Therapies) and propose a quadripartite model of CCBT engagement which should be considered when making decisions about CCBT treatment at an individual or a service level. Their ‘4 Ps’ considers the type of the program, particularities of the problem, user profiles as well as the factors related to the provider. The paper presents the barriers to uptake, engagement and completion of CCBT. In addition, the authors carefully selected and reviewed results reported by the current literature, highlighting the actions which researchers, service developers and providers can take to increase uptake and engagement with the CCBT services.

Cipresso et al. propose the use of Brain Computer Interface (BCI) and Eye-Tracking (ET) technologies for enabling augmentative and alternative communication in Amyotrophic Lateral Sclerosis (ALS). BCI are innovative systems able to generate a control signal from brain responses conveying messages directly to a computer. Eye-tracker systems convey messages from eye-movement to a computer. In this study, the authors explored the use of these two technologies for the cognitive assessment of executive functions in a healthy population and in a ALS patient, also verifying usability, pleasantness, fatigue, and emotional aspects related to the setting.

Serino et al. present so called PsychLog system which is a free open-source mobile experience sampling platform which allows psycho-physiological data to be collected, aggregated, visualized and collated into reports. The authors demonstrated a high accuracy in classifying between relaxing and stressful events, defining the two groups with psychological analysis and verifying the discrimination with physiological measures. A computerized experience sampling method comprising a
mobile-based system that collects psycho-physiological data appears to be a very promising assessment approach to investigate the real-time fluctuation of experience in everyday life in order to detect stressful events.

We hope that this Special Issue will contribute to the exciting developments in the field of mental health and act as a catalyst to work towards the goal of truly personalized e-Mental Health systems.

The Guest Editors (in alphabetic order)
P. Cipresso, M. Hoogendoorn, M. Klein, and A. Matic
Abstract

Help4Mood is a system that supports the treatment of people with depression in the community. It collects rich cognitive, psychomotor, and motor data through a Personal Monitoring System and a Virtual Agent, which is then analysed by a Decision Support System; analysis results are fed back to patients and their treating clinicians. In this paper, we describe how the complex data is managed and discuss ethical issues. Data is stored in functional units that correspond to treatment relevant entities. Custom XML DTDs are defined for each unit, which are used to exchange information between system components. As far as possible, observations and findings are coded using SNOMED CT to ensure interoperability with other applications such as Electronic Health Records.

Keywords: XML, depression, SNOMED CT, decision support

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1. Help4Mood—Supporting People with Depression

Depression is the main cause of disability worldwide [1]. It is characterised by a persistent and intense change of mood which affects behaviour, cognition, and physiology. Two types of depression can be distinguished, a melancholic form where patients’ movements are significantly slowed down, and a non-melancholic form, where movements are not affected or agitated. Slowed movements are reflected in both gross motor function, such as gait, and fine motor function, such as movement initiation and reaction times [2, 3]. They also contribute to slowed speech and a flat intonation [4, 5]. Sleep duration can be either severely reduced (insomnia) or significantly increased (hypersomnia).

At the moment, recovery is monitored infrequently through self-reported patient questionnaires that require the person with depression to remember their symptoms over a period of time that can be as long as two weeks (e.g., PHQ-9 [6]). Those self-reports can be unreliable, especially if the patient is not keeping regular notes or a diary.

Help4Mood enables patients to monitor selected cognitive, behavioural, and physiological aspects of their depression. Patients interact with the system every day to share how they are feeling and complete a few tasks that are informed by cognitive behaviour therapy, such as tracking and challenging negative thoughts. Help4Mood also collects activity and sleep data through a personal monitoring system.

Once every 1–2 weeks, Help4Mood generates a summary of the data that patients will then discuss with the clinician who treats them. This can be a family physician, a psychologist, a psychiatrist, or another health professional with mental health training. The summary includes overall mood, sleep and activity trends, and a list of frequent intrusive negative thoughts, which can be treated using cognitive behaviour therapy. The data generated by Help4Mood will also be useful for reviewing the effectiveness of medication. This design is based on extensive consultation with clinicians and patients in Spain, Romania, and the UK [7]
In this paper, we describe our approach to data management in Help4Mood. We focus on the high-level data structures that form the basis for communicating with clinicians, patients, and other stakeholders.

In Section 2, we give an overview of the Help4Mood system. The basic high-level Help4Mood data structures are described in Section 3. Ethical issues are discussed in Section 4, and provisions for interoperability with Electronic Health Records are outlined in Section 5. Future work plans are summarised in Section 6.

2. Overview of Help4Mood

Help4Mood consists of a Personal Monitoring System, a Virtual agent, and a Decision Support System. Help4Mood is structured around patients’ sessions with the Virtual Agent. Ideally, patients interact with their Virtual Agent daily. The Virtual Agent asks questions, sets tasks, and summarises the results of each session. Sessions can include summaries of activity and sleep patterns. Some of these tasks will yield cognitive data, such as relevant negative automatic thoughts, others are designed to capture relevant neuropsychomotor symptoms of depression.

The sensors of the Personal Monitoring System assess sleep and activity patterns using sleep sensors and a wrist actigraph. While sleep data is collected every night, the wrist actigraph will only be worn for 72 hours at a time. Sessions with the Virtual Agent can include summaries of activity and sleep patterns.

The Decision Support System plans and controls sessions with the Virtual Agent and converts data about the patient’s sleep, motor, speech, and other psychomotor patterns into graphical, textual, and conceptual summaries that can be communicated to clinicians, patients, and electronic health records. As yet, there are very few rules for adjusting medications and interpreting data that could be implemented in a traditional decision support framework [7, 8]. Therefore, the decision support system focuses on trend analysis and planning the interactions between Help4Mood and the patient.

Figure 1 shows the internal structure of Help4Mood. On the left of the graph, we see the sensing / monitoring components, the Virtual Agent, and the Monitoring System. The (Personal) Monitoring System includes the sensors and wireless communication infrastructure.

The structure of the Virtual Agent is more complex. The Virtual Agent consists of a Graphical User Interface (GUI) and a talking head (the “Agent”). Verbal messages are generated by the Natural Language Generation (NLG) component. These messages are displayed by the GUI and spoken by the Agent. Spoken messages are passed to a text-to-speech synthesis engine (TTS) that creates speech with annotations that help synchronise the Virtual Agent’s head and facial movements. The Dialogue System controls the flow of messages, using scripts to ensure the correct wording where clinically relevant.

Data collected via the Virtual Agent and the Personal Monitoring System is processed by the Knowledge Engine. The Knowledge Engine creates summary reports and detects relevant trends about the patient’s mood and behaviour. This information is passed on to the Cognitive/Emotional Model. This component is crucial for planning the interaction between Virtual Agent and user; it passes session plans and information about the intended affective behaviour of the agent on to the Dialogue System, which performs the low-level control.

Communication between the system’s components is implemented using ICE (Internet Communication Engine) as middleware [9]. ICE, which is covered by the GNU public license, has several key advantages. It is independent of programming language and operating system, which is important on a project where components are developed by partners with different IT infrastructures. Since clients do not need to be aware of how the server implements their objects, the server implementation can be changed even after clients have been deployed. Communications between client and server are protected by using SSL (Secure Socket Layer). Last, but not least, ICE produces little overhead.

3. Core Data Structures

All data structures are described using XML. We chose this solution over a relational database, because Help4Mood has a highly modular architecture, and almost all inter- and intra-module communication is based on the exchange of XML messages. Elements are extensively cross-indexed to ensure flexible access to data. Individual components such as the Decision Support System may store data in an internal data base.

The XML elements that are used to capture relevant data are summarised in Table 1. They fall into four main categories, high-level tracking of patient and Help4Mood use, storing monitoring results, managing the interaction between patient and Virtual Agent, and storing the data collected during the interaction. Each set of elements is briefly explained below.
The information contained in these elements is passed onto the Decision Support System, which processes them further. Sensor data are timestamped. Time stamp information is not just used to interpret the data, it is also used to prompt the patient to start a new round of data collection. Specific dialogues are encoded in the VA that tell patients when to put on the actigraph and when to take it off for data collection.

3.3. Managing the Interaction with the Virtual Agent

Sessions typically start with a daily mood check, followed by a diary task. Patients reflect on a specific prompt and write their thoughts into a text field. These entries are stored, but not analysed. Next, patients document negative thoughts relating to this entry, and Help4Mood provides guidance for challenging them. Other activities, such as speech tasks, relaxation exercises, or self-report questions, follow. Finally, the Virtual Agent bids the patient goodbye.

Interactive sessions in Help4Mood need to satisfy four constraints:

**Minimum Requirements:** Patients should complete a daily mood check, which is a validated four-item questionnaire, the CES-VAS-VA [10]. Every fortnight, patients also fill in a formal screening questionnaire, the PHQ-9 [6].

**Sustaining Interest:** Session structure should be varied, with some different tasks each time.

**Adapting To Stamina:** Patient state can vary greatly; on some days, all patients can do is a brief mood check, on other days, they are able to complete a session with four tasks.

**Ensuring Sufficient Data:** Subjective data about the patient such as self-reports and additional psychomotor data such as speech should be collected at least twice a week.

The Decision Support System controls the Virtual Agent’s interaction with the user through events. Events are triggered when their preconditions are fulfilled. They are implemented as interaction tasks. Each task is associated with an emotion that controls the affective behaviour of the Virtual Agent [11] (c.f. Table 1).

The sequence of events and task/emotion pairs that occurred during a session and the data that was generated during a session is stored in a session element for easy reference. This data is used by the Decision Support System to plan further sessions and ensure regular coverage of relevant data.

Table 2 shows the structure of an event element. Each event is linked to a session, a patient, and a specific time within the session. A range of auxiliary elements

### Table 1. Basic Elements of the Help4Mood data structure. Each one is defined using XML.

<table>
<thead>
<tr>
<th>Element</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>High-Level Tracking of Patient and Help4Mood Usage</strong></td>
<td></td>
</tr>
<tr>
<td>User Model</td>
<td>high-level summary of information about the patient</td>
</tr>
<tr>
<td>Adherence</td>
<td>adherence of patient to Help4Mood; can refer to sessions, tasks, and monitoring</td>
</tr>
<tr>
<td>Report</td>
<td>summary report for clinician</td>
</tr>
<tr>
<td><strong>Managing the Results of Monitoring</strong></td>
<td></td>
</tr>
<tr>
<td>Monitor. Data</td>
<td>set of data points</td>
</tr>
<tr>
<td>Measure</td>
<td>high-level measure computed from monitoring data</td>
</tr>
<tr>
<td>Score</td>
<td>score on stand. questionnaire</td>
</tr>
<tr>
<td><strong>Managing the Interaction with the Virtual Agent</strong></td>
<td></td>
</tr>
<tr>
<td>Session</td>
<td>content and results of a session with the Virtual Agent</td>
</tr>
<tr>
<td>Event</td>
<td>event triggered by the Decision Support System during a session</td>
</tr>
<tr>
<td>Task</td>
<td>task that is performed by the patient during a specific session</td>
</tr>
<tr>
<td>Emotion</td>
<td>emotion used by Virtual Agent during interaction with patient</td>
</tr>
<tr>
<td><strong>Storing Information Collected During Interaction</strong></td>
<td></td>
</tr>
<tr>
<td>Diary</td>
<td>information on diary entries</td>
</tr>
<tr>
<td>Speech</td>
<td>changes in speech</td>
</tr>
<tr>
<td>Neg. Thought</td>
<td>frequency of negative automatic thoughts</td>
</tr>
<tr>
<td>Self-Report</td>
<td>results of self-report questions</td>
</tr>
<tr>
<td>Exercise</td>
<td>completion of exercise</td>
</tr>
</tbody>
</table>

3.1. High Level Tracking

The three high-level tracking elements in Table 1 summarise relevant information about the patient and system usage and store the regular reports generated by the system. Patient information, which is stored in the user model, includes basic demographics (occupation, gender, age) as well as current depression scores. The user model also includes information about the background photo chosen by the user, the avatar the user has chosen, and their preferred interaction style and personality (friendly or formal). As for reports, only official reports that are sent to the clinicians and can be discussed in patient/clinician meetings are stored. The feedback given to the patient at the end of each session is not saved, because it can be reconstructed easily.

3.2. Monitoring

The next two elements in Table 1 are used to describe high-level monitoring data. While the measure element covers specific analysis results, the monitoringdata element contains the measures obtained during a session.
Table 2. The Event class

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>{1,2,3,4}</td>
<td>Event type as classified by data source</td>
</tr>
<tr>
<td>Session</td>
<td>timestamp</td>
<td>Session ID</td>
</tr>
<tr>
<td>Patient</td>
<td>alphanumerical</td>
<td>Patient ID</td>
</tr>
<tr>
<td>Description</td>
<td>descriptor</td>
<td>Formal description of the event</td>
</tr>
<tr>
<td>Generated</td>
<td>timestamp</td>
<td>Time at which the event was generated</td>
</tr>
<tr>
<td>Preconditions</td>
<td>list of conditions</td>
<td>Pre-conditions that trigger the event.</td>
</tr>
<tr>
<td>Postconditions</td>
<td>list of conditions</td>
<td>Findings or observable entities</td>
</tr>
</tbody>
</table>

is used to specify events. Descriptors link Events to a formal code that describes the underlying procedure and can be exported to external systems. Preconditions and postconditions are described using condition elements that consist of (Property, Operator, Value)-tuples. Preconditions trigger events, postconditions describe the outcomes of an event.

During most tasks, the system collects rich information about the patient’s cognition and current psychomotor functioning. Relevant high-level data is encoded in the diary, speech, selfreport, and negative thought elements.

4. Privacy, Security, and Ethical Considerations

The data that Help4Mood logs about a person’s activity and mood is private and confidential. It is therefore imperative that it is stored securely. Since we do not assume that Help4Mood’s users have a broadband internet connection, all data is initially stored in a single encrypted partition on a dedicated laptop, which can only be used to run the Help4Mood application. Raw data can only be accessed by the clinicians and technical support personnel that give out the Help4Mood kit, which consists of sensors and laptop.

The baseline solution for transmitting data to the relevant health care professionals is to send an encoded PDF with a summary of relevant trends via e-mail. This is the most portable solution, and it does not require the clinician-side Electronic Health Record / Electronic Medical Record system to support standards such as HL7. For systems that do support HL7, the PDF will be embedded in a HL7 CDA record.

The ethical considerations around the data that is collected can be summarised by one question: Will the system be able to pick up indications of suicide or self-harm, and if yes, what should the reaction be? Since the cost of failing to detect suicidal or self-harm tendencies far outweighs the cost of false alerts, it is highly likely that many false alarms would be generated, which would increase the burden on the treating clinical team. Therefore, we decided to analyse only data that does not contain any unambiguous pointers to self-harm or suicide. This means that diary data is excluded from analysis, because people can explicitly describe suicidal ideation there. There is one exception: The PHQ-9 questionnaire, which is administered every fortnight, includes a question on self-harm or suicidal ideation; if the answer indicates cause for concern, users will be taken off the Help4Mood intervention immediately because they will need closer supervision.

5. Electronic Health Record Integration

In order to foster interoperability with IT systems across the European Union, it is important to use a standard vocabulary to describe findings, procedures, and actions. For Help4Mood, we chose the international Core Release of SNOMED CT [12]. SNOMED CT is a highly complex, extendable clinical vocabulary that can be integrated with standards such as HL7 [13], which Help4Mood will support.

Most of the SNOMED-CT concepts used in Help4Mood come from the Clinical Finding hierarchy. Clinical findings are the outcome of assessments, observations, or judgements. For example, if the sleep sensor data indicate that the patient tossed and turned frequently at night, this can be encoded as the Clinical Finding “restless sleep”.

Another class of concepts that are relevant to Help4Mood are Procedures. In SNOMED-CT, procedures are activities that occur at a specific time and involve the patient and include education and administration. Examples of procedures are guiding the patient through a relaxation exercise or showing the patient a list of activities that were identified as comforting.

A question or a procedure that produces a result is an Observable Entity. For example, “gender” is an observable entity, while “female gender” is a finding. While many demographic characteristics of patients are covered by Observable Entities, other information such as occupation is encoded using concepts from the Social Context hierarchy.

Modelling questionnaires in SNOMED-CT requires concepts from three different hierarchies. The questionnaires as measurement instruments are part of the Staging and Scales hierarchy. Questionnaire scores are modelled as observable entities, and the interpretation of questionnaire scores is encoded as a clinical finding.

For example, assessing a patient using the Beck Depression Inventory (BDI, [14]) is a procedure that has the Concept ID 446765009. The patient’s score on the BDI is an observable entity with the Concept ID 446053003, and the BDI itself is an assessment scale with the Concept ID 273306008. The finding that
is associated with a patient’s score is encoded using one of the subtypes of the clinical finding “Depressive Disorder” (Concept ID 35489007).

We defined our own codes only if the relevant findings, observable entities, or procedures were not included in SNOMED-CT. In all cases, these codes are linked to a parent concept in SNOMED-CT. For example, unlike the Beck Depression Inventory, none of our depression measures are modelled explicitly in SNOMED-CT, although they are well-known and validated. Therefore, we assigned system-specific codes to the resulting scores and linked them to relevant parent concepts. For example, the PHQ-9 score is an Observable Entity which is in an is-a relation with the SNOMED CT concept Mental state, behavior / psychosocial function observable. The interpretation of cognitive games is also not covered. While the scores themselves are observable entities, changes in scores as well as relevant trends are modelled as findings. Table 3 summarises the implementation of these examples.

While information such as questionnaire scores can be stored more or less directly, concepts such as “restless sleep” require interpretations of sensor data. The Decision Support System will implement algorithms for mapping raw sensor data to these categories, which will be refined as data is collected in user studies and trials.

6. Taking Help4Mood Further

The data management approach outlined here provides a detailed, systematic representation of all of the relevant high-level information that Help4Mood collects about a patient with depression. It was designed for easy maintenance and maximum interoperability with Electronic Health Records. New sensors and interaction modules can be integrated easily. No new elements are required for additional sensor data, and we anticipate that for most exercises, we will only track completion.

We are planning three trials of the Help4Mood system. These will be iterative, starting with a bare-bones system and progressively adding functionality. At this stage, the most important function of the data structures is to make data readily accessible for future analysis. Given the relative lack of information on the sleep and activity patterns of people with depression in the community [8], one of the key important contribution of Help4Mood will be clean, usable data. Data will be summarised using visualisations and natural language summaries.

In future iterations of Help4Mood, the DSS will be extended to suggest activities or provide brief psychoeducation that reinforces the “homework” that clinicians often give to patients. We also plan to add HL7 integration, and refine the elements and clinical vocabulary described here to provide a more detailed ontology for interoperability.

References


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**Table 3.** Anchoring New Concepts in SNOMED-CT. HM: Help4Mood concept, is-a: linked SNOMED-CT concept

<table>
<thead>
<tr>
<th>Procedure</th>
<th>HM</th>
<th>Finding</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>999991021</td>
<td>Assessment using PHQ-9</td>
</tr>
<tr>
<td></td>
<td>44536608</td>
<td>Assessment using assessment scale</td>
</tr>
<tr>
<td>Observable</td>
<td>H4M</td>
<td>PHQ-9 score</td>
</tr>
<tr>
<td>Entity</td>
<td>is-a</td>
<td>36387007</td>
</tr>
<tr>
<td>Finding</td>
<td>is-a</td>
<td>999992011</td>
</tr>
<tr>
<td></td>
<td>248536006</td>
<td>Finding of functional performance and activity</td>
</tr>
</tbody>
</table>


Increasing engagement with computerised cognitive behavioural therapies

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Abstract

The evidence base for computerised cognitive behavioural therapy (CCBT) for common mental health problems has expanded rapidly in recent years. Reviews and meta-analyses have produced promising findings with regard to CCBT’s effectiveness and acceptability, but developing and supporting effective and sustainable models of CCBT service implementation remains a challenge. This paper considers CCBT usage and explores the uptake of, and engagement with, CCBT. Recent literature on the topic of engagement with CCBT is summarised. Factors relating to discontinuation of use or ‘drop-out’ are also explored. Drawing on this evidence base we propose a simple ‘4 Ps’ model of engagement factors: the programme, the problem, the person and the provider. We highlight some actions that researchers, service developers and providers can take that might increase uptake and engagement within the CCBT services that they provide. Managing expectations and promoting hope in both service users and providers are emphasised.

Keywords: Computerised CBT, e-mental health, uptake, engagement, drop-out

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1. Introduction

The evidence base for computerised cognitive behavioural therapy (CCBT) in common mental health problems is expanding rapidly. Recent reviews and meta-analyses have produced promising findings regarding CCBT in terms of effectiveness and acceptability (e.g. Andrews, Cuijpers, Craske, McEvoy, & Titov, 2010; Barak, Hen, Boniel-Nissim, & Shapira, 2008; Cuijpers et al., 2009, 2008; Marks, Cavanagh, & Gega, 2007; Newman, Szkodny, Lieta, & Przeworski, 2011; Richards & Richardson, 2012).

The attractions of CCBT as a treatment option for common mental health problems include its developing evidence base, relative advantage in terms of cost-effectiveness, increased availability and accessibility of services (anytime, anywhere), and the congruence of CCBT services with various other contemporary healthcare drivers such as increased choice, reduced stigma, patient empowerment and self-care.

In the United Kingdom, the National Institute for Health and Clinical Excellence (NICE, 2006; 2009) recommends CCBT as a treatment choice for panic, phobia and persistent sub-threshold and mild-to-moderate depression within the National Health Service (NHS). CCBT is offered to clients with common mental health problems in a range of contexts including primary care, specialist CBT therapy clinics, Increasing Access to Psychological Therapies (IAPT; Department of Health, 2008) services and dedicated e-health clinics, and has now reached many thousands of users. Similar guidelines to healthcare providers and expansions in computerised and internet-based interventions are seen internationally.

Whilst CCBT has been demonstrated to be effective in a range of settings, developing and supporting effective and
sustainable models of CCBT service implementation in routine care presents a challenge – not least due to barriers to uptake and engagement.

This paper considers CCBT usage and explores the challenges to uptake and engagement with CCBT. It aims to summarise recent literature regarding factors influencing engagement with CCBT and presents a simple ‘Four Ps’ model of engagement factors associated with i) the programme, ii) the problem, iii) the person, and iv) the provider. Drawing upon this model, this paper contributes to the literature by highlighting some actions that researchers, service developers and providers can take to increase uptake and engagement with the CCBT services that they provide.

2. Computerised Cognitive Behavioural Therapies (CCBT)

Computerised Cognitive Behavioural Therapy (CCBT) is a generic term that is used to refer to a number of methods of delivering cognitive behavioural therapies (CBT) via an interactive computer interface that uses patient input to make at least some psychotherapy decisions (Marks, Shaw, & Parkin, 1998).

Whilst internet-based interventions for mental health are not limited to cognitive-behavioural approaches (e.g. Paxling, 2011), CBT is the most commonly computerised psychotherapeutic approach within the research literature. This is because the evidence base for manualised CBT for common mental health problems is well developed and appears robust (Roth & Fonagy, 2005). Moreover, the manualised, structured and collaborative approach and techniques of this model are well matched to adaptation into computerised methods of delivery.

Whilst CCBT programmes vary in their problem focus, structure and style, some common features are observed between programmes. Most include some elements of psychoeducation relating to the presenting problem and the CBT approach to making sense of it. Most also include some assessment of current problems with feedback, repeated assessment to facilitate change monitoring and feedback throughout the course of the programme. Most programmes promote the identification of target problems and therapeutic goals. They also typically involve action planning and guide the user through cognitive-behavioural change techniques (e.g. behavioural activation, problem solving, identifying and challenging negative automatic thoughts, graded exposure etc.). Finally, most programmes encourage the user to put new learning into practice via ‘homework’ tasks between sessions. Such tasks might take the form of diary keeping, thought recording, approach activities or behavioural experiments.

CCBT programmes are accessed on a variety of devices (PC, tablet, smart phone) usually from an internet server, although some stand-alone programmes are run direct from the device without internet connectivity.

CCBT programmes are typically designed to be used either as ‘pure self-help’, without any professional support, or ‘guided self-help’, in which the user is supported by a technician, coach or therapist throughout their use of the programme. Such support may be delivered in person or remotely via telephone, email or other messaging services. There is some evidence that outcomes for CCBT are improved by the provision of brief human support (Gellatly et al., 2007), particularly in the case of users with more complex needs and those suffering from depression (Newman et al., 2011).

2.1. The evidence base for CCBT

Depression

CCBT programmes have typically, although not exclusively (cf. Titov et al., 2011; Proudfoot et al., 2003), been designed to target single diagnostic entities. In the case of depression, a number of programmes have been designed to target this disease specifically, and have been evaluated as options for the treatment of both sub-clinical and clinical depression. Meta-analyses have consistently indicated that use of CCBT programmes is associated with significant reductions in measured depressive symptoms (Barak et al., 2008; Andrews et al., 2010; Richards & Richardson, 2012; Spek et al., 2007).

A recent meta-review paper cautiously concludes that there is evidence that “certain CCBT packages, specifically Moodgym, Beating the Blues and Colour Your Life, can have a positive effect on symptoms of depression” (p.5, Foroushani, Schneider & Asserah., 2011), although questions about the methodological rigour of both the original research papers and summary papers interrogated is foregrounded in this analysis.

For depression specifically, CCBT programmes offered with support yield better outcomes than those without (Richards & Richardson, 2012). Newman et al. (2011) has argued that in the case of clinical levels of depression, supported options are optimal, however, evidence of some effect in unsupported and very briefly supported CCBT programmes for depression have also been demonstrated (e.g. Richards & Richardson, 2012).

Anxiety

A number of CCBT programmes for both general problems of anxiety and specific anxiety disorders have been developed and evaluated. Meta-analyses have consistently indicated that CCBT programmes are
associated with significant reductions in measured anxiety symptoms (Andrews et al., 2010; Barak et al., 2008; Cuijpers et al., 2009; Spek et al., 2007).

A recent review article has concluded that for motivated clients with anxiety, pure self-help, or programmes with very limited support can be effective, although programmes with more support are associated with greater engagement (Newman et al., 2011).

3. User engagement with CCBT

Taken together, the CCBT literature strongly suggests that such programmes can offer significant benefits for the prevention and treatment of common mental health problems and have the potential to extend the reach of evidence based psychological interventions. Some programmes may attract many users, but evidence to date suggests that a significant number of people may be unwilling to engage with CCBT programmes as a treatment option for anxiety or depression, or having started, use them only briefly, and with little or no benefit. Identifying and understanding barriers and promoters of uptake, engagement and completion (see Figure 1) and the mechanisms by which drop-out occurs is a key priority for contemporary research into CCBT.

3.1. Uptake rates

Uptake rates of CCBT in the real world may be difficult to establish, as markers of initial interest (e.g. following a web-link, or a brief discussion of treatment options with GP) are rarely recorded. Where uptake rates have been measured in the context of research studies, wide variance has been noted. For example, Whitfield et al. (2006) reported on low uptake (26%) of an offer of CCBT to a waiting list group in a clinical psychology service. In contrast, Learmonth, Trosh, Rai, Sewell, & Cavanagh (2008) reported much higher uptake – 67% (555) of 829 people offered CCBT as a first-step of care within a specialist CBT service. A review of uptake rates in CCBT research trials found that just 38% (range 4% - 83%) of those invited to a CCBT research trial start the programme (Waller & Gilbody, 2008). These large differences between studies may indicate complex influences on uptake at work.

3.2. Engagement and Adherence

There is no agreed definition of engagement with CCBT. In between logging-on and active completion of a self-help intervention lie a number of other possible indicators of engagement. These include repeat programme visits, module completion, accessing support sessions, reading self-help materials, completing in-session activities online, engaging in between-session homework activities.

Individual studies have reported on various CCBT engagement metrics and their predictors (e.g. Neil et al., 2009), but there is little conclusive evidence of what markers of engagement are most significant or how to reliably predict them.

3.3. Drop-out

Measures of disengagement from self-help interventions tend to focus on “drop-out” - or non-completion - of a planned treatment program. Whilst “self-pacing” is one treatment level benefit often assigned to the use of self-help materials, most CCBT programs are designed to be used in a structured format and have a proscribed number of modules. In the case of guided CCBT this may be coupled with a predetermined number of support contacts.

A number of review papers have estimated the average attrition or drop-out rate from computer-based therapies including CCBT. Again, large differences between studies are found. In a meta-analytic study Kaltenthaler et al. (2008) reviewed 16 trials of CCBT and found a mean drop-out rate of 31.75% (SD 16.5%, range 0-75%). Waller and Gilbody (2008) found a median of 56% treatment starters completed a full course of CCBT in the trials they reviewed. Drop-out rates may be higher in real world and pragmatic research contexts than in strictly controlled trials.

For depression, drop-out rates for unsupported CCBT appear to be higher than for supported CCBT (Richards & Richardson, 2012). Drop-out rates for open-access CCBT programmes appears much higher than access during research trials. Less than 1% of unsupported open access users having been reported to complete CCBT for depression (Christensen, Griffiths, Groves, & Korten, 2006), with similar figures recorded for panic (Farvolden, Denissof, Selby, Bagby, & Rudy, 2005).

Reasons for drop-out might include dissatisfaction with treatment allocation, practitioner advice to discontinue, symptom deterioration or illness, move of house and work commitments (Proudfoot et al., 2003). However, it is
acknowledged that not all disengagement from self-help programs is counter-therapeutic, and in some cases it may represent a self-determined therapeutic early ending based on early gains, symptom improvement, or uptake of alternative services. Further investigation of the actions and experiences of this under-researched population may enhance our understanding of engagement processes in CCBT and e-health more broadly.

4. The Four P’s model

The potential clinical benefit of CCBT programmes for common mental health problems is supported by a large number of original studies and meta-analyses (see above). Additional benefits have been hypothesised including service and user cost-savings, extended reach of services, increased access, reduced user stigma, increased user empowerment and learned resourcefulness. However, translating these potential benefits into practice may be limited by barriers to uptake, engagement and completion. This presents a challenge for CCBT stakeholders including programme developers, practitioners and service providers.

We present a simple quadripartite model that describes each of the core factors associated with engagement and disengagement with CCBT (Figure 1). Evidence of the importance of each core factor for engagement is described in this section. The section concludes with advice to CCBT stakeholders on how to adopt this model in decision making about CCBT.

4.1. Programme factors

A review of the literature suggests that CCBT treatments may vary in a number of ways which might influence engagement. These include programme content, structure, length, content, style, and interactivity.

Content

In terms of content, NICE (2009a) recommends that self-help programmes ‘based on the principles of CBT’ are recommended for the treatment of depression. This should include both the specific tools and techniques of evidence based CBT interventions, but also the common factors which may promote user engagement.

Few studies have compared CBT techniques delivered in a CCBT format head-to-head. Christensen, Griffiths, Mackinnon and Brittcliffe (2006) found that two sessions of CBT techniques with or without the addition of behavioural strategies resulted in the reduction of depression.

A recent qualitative analysis has indicated that CCBT programmes for depression are characterised by substantial evidence of built-in common factors (e.g. generating hope, empathy and warmth, collaboration, feedback; Barazzone, Cavanagh & Richards, 2012). While theory and research suggest that such factors ought to promote engagement and decrease drop-out, further research is required to ascertain whether this is actually the case.

Structure

Relatively little is known about the impact of programme structure on treatment uptake or drop-out. There is some evidence of improved adherence with greater structure (Celio, Winzelberg, Dev, & Taylor, 2002). Preliminary evidence from Andersson (2010) suggests both ‘pick and mix’ and ‘set menu’ models can work, but to date no head to head trials have been published and the best available evidence is for structured programmes which involve ‘taking the user by the hand’ through a treatment programme (Kraft, Drozd, & Olsen, 2009).

Length

Relatively little is known about the impact of the length (or number) of sessions of self-help treatment on treatment uptake or dropout, although longer programmes may have suffer from their greater opportunity for disengagement. At the brief-intervention end of the scale, Christensen, Griffiths, Mackinnon and Brittcliffe (2006) found no difference in treatment completion between patients randomised to 1, 2, 3, 4, or 5 sessions of internet based self-help (mean rate of completion 20%).
Many CCBT programmes are designed in sessions based on a typical therapy session (e.g. about 50 minutes). However, actual use of these programmes suggests users may prefer to digest the programmes in briefer units, and that CCBT use is more aligned with everyday internet use than the classical model of face-to-face therapy. The average length of stay on MoodGym is 9.5 minutes (Christensen, Griffiths, & Korten, 2002). The average number of “log-ons” to an 8 session programme is 26 (Colour Your Life), and the average number of sessions completed is 3.4 per user; De Graaf et al., 2009). The average length of stay on internet intervention sites may also be shorter outside of research trials (Wanner et al., 2010).

### Style and interactivity

Lewis, Pearce and Bisson (2012) have recently reported that the outcomes of self-help interventions for anxiety are enhanced by the presentation of multi-media or web-based materials. But limited research to date has robustly explored the impact of self-help style, media or interactivity on CCBT engagement (or outcomes). Christensen, Griffiths and Jorm (2004) found similar effects of an interactive internet CBT programme (MoodGym) and a non-interactive internet psychoeducation site (BluePages) on depression symptoms, but higher rates of drop-out in the CCBT group. Further research is needed to unpack the treatment and retention effects of interactivity and media.

The enormous scope for potentially engagement-enhancing features and there may be many benefits to developing a user interface with this in mind. Such interfaces should be matched to the users preferences and needs: ‘user-friendly and not over technically advanced’ (Andersson, Carlbring, Berger, Almlov, & Cuijpers, 2009). While in need of further research, the alliance features of self-help materials are highlighted as an important area of potential development in terms of promoting engagement (Barazzzone, Cavanagh & Richards, 2012).

#### 4.2. Problem factors

The presenting features of clinical problems such as anxiety and depression may in themselves contribute to engagement with CCBT programmes. In addition, problem severity, comorbidity and complexity might contribute to an understanding of why people engage with or disengage from CCBT.

### Anxiety and depression

Characteristic features in the clinical presentation of anxiety and depression might contribute to potential users’ ability to initially take-up and persevere with self-help CCBT interventions. Cardinal symptoms of depression such as poor concentration and a sense of hopelessness may appear contraindicated for active engagement with self-help CCBT. Moreover, common features of depressive disorders such as difficulties in goal setting and engagement, and loss of agency (helplessness) might contribute to difficulties in working through self-help change strategies. Similarly, anxious preoccupation and habitual avoidance seem poorly matched to experiences for new learning and taking therapeutic “risks” in self-help programmes. Limited research to date has explored how such problem features might be associated with CCBT engagement, and further research is recommended.

### Severity, comorbidity and complexity

Relatively little is known about the impact of problem severity, comorbidity or complexity on engagement or disengagement with CCBT. CCBT is typically recommended for problems of mild-to-moderate severity, although there is an absence of evidence advocating the exclusion of more severe presentations. CBT is recommended by NICE for the treatment of depression in the context of chronic physical illness (2009b). There is also some evidence that CCBT may be effective for depression with comorbid substance misuse (Kay-Lambkin et al., 2009).

However, there is some evidence that comorbid diagnosis of personality disorder may be related to disengagement from self-help interventions. For example, Andersson, Carlbring and Grimaud (2008) found personality disorder to be a negative predictor of outcome a self-help treatment for panic, mirroring Persons, Burns, and Perloff’s (1988) study of predictors of the success of cognitive therapy for depression, which indicated that a comorbid diagnosis of personality disorder predicted premature ending of face-to-face therapy. Andersson et al. (2008) suggest that self-help treatment options offer less room for repair of misunderstandings in communication, which may be particularly important for maintaining engagement in people with personality disorders.

Problem complexity might not exclude people from possible benefit of CCBT for a target problem, but a more sophisticated level of service may be required to support this in practice.

### 4.3. Person factors

#### Demographic variables

Demographic variables such as age, gender, and level of education have been considered as factors that might influence CCBT engagement.

Proudfoot (2004) has speculated that computer based self-help may be a particularly acceptable treatment option for
young males, although this review found no studies to support differential levels of uptake of CCBT in this group. Indeed some evidence suggests that female users may be more likely to adhere to a self-help programme (Neil, et al., 2009) and find CCBT programmes more acceptable than do males (Cavanagh et al., 2009).

Kaltenthaler, Parry, & Beverley (2004) speculated that for older people, in the case of self-help treatments, “computer use may be unacceptable” (p. 73). However, evidence from a “willingness to engage” questionnaire study with older adults (aged 65+) indicated that almost half would be interested in using CCBT and would be willing to learn the computer skills required (Elsegood & Powell, 2008). A recent systematic review concluded that older adults are an under researched group who may potentially benefit from CCBT programmes for depression (Crabb et al., 2012).

Waller and Gilbody (2008) note a bias towards higher levels of education and higher social class in participants of research studies of CCBT in comparison to population averages for primary care populations, which suggests that these self-help strategies (or at least engagement in research trials regarding them) may not be equally accessible or attractive as treatment options across the population. This is supported by evidence from studies of face-to-face CBT where economically disadvantaged groups tend to experience more barriers to treatment engagement and adherence than other groups (Mukherjee et al., 2006).

Literacy and computer-literacy have been considered as possible barriers to accessibility or suitability of self-help CBT approaches (McLeod, Martinez, & Williams, 2009). The ability to read and write in the language in which CCBT materials are scripted at a level matched to the materials is pre-requisite to their accessibility.

Waller and Gilbody (2008) found that participants in studies of CCBT tended to have high levels of computer literacy in comparison to the general population, suggesting that potential users with lower levels of computer literacy may opt-out of such treatments. Access to a computer at home, in a health care practice or other location (library, internet cafe etc.) is also requisite to CCBT use.

Student samples have been specifically targeted as a potential market for self-help interventions, particularly computerised therapies with mixed results (Lindveldt et al., 2008; Mitchell & Gordon, 2007; Tarrier, Liversage, & Gregg, 2006). Lindveldt et al. (2008) speculated that internet based self-help programmes may be particularly attractive to young adults in the student population who are at high-risk of common mental health problems but may not seek out help from traditional (face-to-face) mental health services. The results of their study of Norwegian students indicated that many participants reporting an unmet need for help with psychological problems expressed a positive attitude to the experience of accessing an internet based self-help CBT programme for depression. In contrast, two studies exploring attitudes to computer based self-help CBT in UK student populations found that such programmes fared poorly, being rated 12 out of 14 in order of personal preference for treatments of posttraumatic stress disorder (Tarrier et al., 2006) and as the preferred treatment choice for depression for only 10% of participants (Mitchell & Gordon, 2007). However, the computer-aided therapy programmes described in these studies had a limited evidence base, and prior knowledge of computer-based therapies in the samples was low. Attitudes toward computer-aided therapy for depression improved somewhat after a demonstration of a CCBT programme (Mitchell & Gordon, 2007).

User expectations
Pre-therapy expectations about the nature of CCBT treatment and its likely benefits will influence a potential user's willingness to engage with that treatment and their hopefulness about the outcomes of engagement. Where treatment credibility and outcome expectations are high, programme uptake and continuation is more likely (e.g. Longo, Lent, & Brown, 1992). In an open study of a CCBT programme, pre-treatment expectancies predicted programme completion, but not outcomes. (Cavanagh et al., 2009).

Murray et al. (2003) found that potential users who don't take up the offer of computer-based therapy expected it to be less useful than treatment starters and had a range of concerns and misunderstandings about the programme. Users' ‘mental model’ of accessing psychological support or therapy may differ from a guided self-help programme option (e.g. 'I didn’t know there would be homework'; Macdonald et al., 2007), and should be elicited and clarified in a discussion of treatment choice regarding CCBT.

Lack of programme credibility and lack of motivation were identified as barriers to engagement with self-help materials by CBT practitioners surveyed by McLeod et al. (2009). As poor motivation may be a clinical feature of depressive disorders this may make engagement with CCBT programmes targeting depression particularly challenging.

Future research needs to better explicate the mechanisms of individual differences in preferences, motivation, and adherence with CCBT. Face-to-face therapy literature suggests that personality and relationship factors such as attachment style influence therapeutic process (Slade 1999; Eames & Roth, 2000) and outcomes (Tasca et al., 2006). Pilot data suggest that attachment style might be associated with preferences for different kinds of
4.4. Provider factors

A review of the literature suggests that CCBT provider contexts may vary in a number of ways which might influence engagement. These include the treatment location, provider attitudes, the amount of support, who offers support and the type of support offered.

Location

There is evidence that CCBT can be an effective treatment option for common mental health problems when made available in a broad range of provider services including primary care (Proudfoot et al., 2004), secondary care (Ormrod et al., 2010), specialist CBT services (Learmont et al., 2008), service-user led third sector organisations (Cavanagh, Seccombe, & Lidbetter, 2011) and dedicated e-health services (e.g. Andersson et al., 2008). To date, no studies have robustly compared different service models to provide evidence of optimal delivery contexts.

Wherever accessed, the “positioning” of self-help services may be important for promoting and maintaining engagement. Williams & Martinez (2008) have noted that where computer-aided therapy programmes are positively introduced as a “first step of care” they tend to have a far higher take-up than in situations where self-help is simply offered as a 'stop-gap' option to persons who already have the offer of face-to-face therapy with a practitioner.

Provider attitudes

Provider attitudes to self-help in general and CCBT specifically might influence the availability of self-help materials and support services, as well as the accessibility of these for clients.

Two surveys of accredited CBT therapists have found that most therapists offer some self-help materials to clients, and have a positive attitude towards their use. However, just one third had accessed training in the use of self-help materials. Those who had received training rated the helpfulness of self-help materials more favourably and tended to offer them to patients more frequently (Keeley, Williams, & Shapiro, 2002; McLeod, Martinez & Williams, 2009).

In their review of the literature on barriers to uptake of computer-based therapies in particular, Waller and Gilbody (2008) concluded that clients are more positive about computer-based therapies than are professionals. This is supported by evidence from a survey of CBT practitioners who expressed doubts about the acceptability of CCBT programmes to users (Whitfield & Williams, 2004). Few therapists in this survey (<3%) offered computerised self-help materials to clients either as a stand-alone treatment or an adjunct to face-to-face therapy, despite emerging evidence of effectiveness.

Amount of support

Reviews and meta-analysis of CCBT have consistently demonstrated that supported programmes yield greater clinical benefit than unsupported programmes. In addition, supported programmes are associated with higher levels of completion (e.g. Newman et al., 2011; Richards & Richardson, 2012; Spek et al., 2007).

Where support is offered, this ranges from a few minutes to several hours of therapist support per user during the course of the programme. Palmqvist et al (2007) reported a linear, positive relationship between support time and therapeutic outcomes, but to date the relationship between support time and engagement remains unclear. Further research exploring optimal support time for different groups of clients, using different CCBT programmes in different contexts needs to be established.

What kind of support is needed?

Baguely et al. (2010) offer ‘good-practice guidelines’ for self-help services, highlighting the key role of support workers in identifying problems and goals to work on, helping the user to choose appropriate self-help materials, supporting them in their efforts to change and the monitoring and review of progress. The development of a new ‘therapeutic relationship triangle’, between the user, supporter and CCBT programme warrants future research (Cavanagh, 2010).

Kenwright (2010) recommends brief (no longer than 20 minutes), structured, scheduled support sessions for guided self-help including CCBT. The content of support sessions should include collaborative agenda setting, monitoring and review of clinical measures, goals and homework activities, positive feedback on any progress, identification and discussion of obstacles, problem solving support, weekly collaborative goal-setting, and homework activities with planning for potential problems. This kind of support has been demonstrated to be effective in both research studies and real-world contexts offering CCBT. In addition to regular human support, log-on reminders sent by post-card, email,
telephone or SMS may have an impact on program adherence and on outcome (Clarke et al., 2005).

Who should provide support?
There is evidence that CCBT can be effectively supported by a range of professionals and para-professionals, with limited evidence to differentiate between supporter type in engagement outcomes. In one study of CCBT for depression, briefly trained ‘technicians’ were found to offer outcomes as effective as experienced clinicians when offering similar levels of support. Dropout rates were also similar in both groups (Robinson et al., 2010).

4.5. The fifth ‘P’: Putting it all together
The 4 P’s model of CCBT engagement highlights four core factors associated with CCBT engagement (and disengagement): person, programme, problem, and provider factors. The reliability and validity of the ‘4 Ps’ model should be evaluated in future research. Each factor is important in its own right, but is also likely to interact with each other factor to influence engagement processes and outcomes. Further research is needed to better understand the additive and interactive effects of these factors on engagement outcomes. CCBT stakeholders are advised to consider a multifactorial approach to understanding engagement when making treatment decisions at an individual and service level.

5. Final comments
The evidence base for CCBT for common mental health problems is promising, but developing and supporting effective and sustainable models of CCBT service implementation remains a challenge – not least due to barriers to uptake, engagement and completion. This paper has explored some of the knowledge base relevant to user engagement with CCBT programmes, and has presented a quadripartite model of CCBT engagement which should be considered when making decisions about CCBT treatment at an individual or service level.

The ‘four Ps’ model considers person, programme, problem and provider factors that may influence engagement with CCBT. This model may be used as a tool to support the development and implementation of CCBT programmes and services. Systems which take each of these factors, and their interaction, into account are likely to benefit from increased uptake and engagement and reduced drop-out. Actions to optimise engagement outcomes may improve the reach and benefit of CCBT for many people with common mental health problems.

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Declaration of interest
Kate Cavanagh is a consultant to, and Abigail Millings employed by, Ultrasis UK Ltd, which markets Beating the Blues, an internet based programme for depression and anxiety.

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Increasing engagement with CCBT


Cognitive assessment of executive functions using brain computer interface and eye-tracking

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Abstract

New technologies to enable augmentative and alternative communication in Amyotrophic Lateral Sclerosis (ALS) have been recently used in several studies. However, a comprehensive battery for cognitive assessment has not been implemented yet. Brain computer interfaces are innovative systems able to generate a control signal from brain responses conveying messages directly to a computer. Another available technology for communication purposes is the Eye-tracker system, that conveys messages from eye-movement to a computer. In this study we explored the use of these two technologies for the cognitive assessment of executive functions in a healthy population and in a ALS patient, also verifying usability, pleasantness, fatigue, and emotional aspects related to the setting. Our preliminary results may have interesting implications for both clinical practice (the availability of an effective tool for neuropsychological evaluation of ALS patients) and ethical issues.

Keywords: cognitive assessment, executive functions, brain computer interface, eye-tracking.

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1. Introduction

Some of the most consistently reported cognitive changes in Amyotrophic Lateral Sclerosis (ALS) regard frontal executive functions, in particular verbal fluency, together with attention, working memory, planning and abstract reasoning [1- 6]. However, the assessment of cognitive impairment still remains a problematic issue in ALS patients, because of the possible presence of severe physical disabilities, including movement impairment, paralysis in the advanced stages and dysarthria, which interfere with the outcome of traditional neuropsychological testing. In fact, all standard assessment tools involve verbal or motor responses.

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New technologies to enable communication have been recently used in several studies. Among these methods, Brain Computer Interface (BCI) and Eye Tracking (ET) are the most promising technologies. BCI uses neurophysiological signals as input commands to control external devices, while ET allows the measurement of eye position and movements. However, a comprehensive battery for cognitive assessment has never been implemented with these methodologies.

With regard to ET, to date, no applications have been developed, using it as a communication device in order to administer traditional cognitive tasks to patients.

The main disadvantage in the use of ET systems is that they require preserved ocular mobility, and the absence of relevant visual deficits; the former may be lost or altered in the final stages of the disease, and the latter may be present in patients of advanced age, thus forbidding the use of this device. So, in case of impaired ocular mobility, there is the
need of a more direct interface between voluntary cortex activity and a technological device. BCI may offer an interesting answer to this issue with a growing number of different paradigms proposed. The most frequently used is the P300, an event related potential (ERP) elicited by infrequent task stimuli, that occurs 200-700 ms after stimulus onset; it is typically recorded over central-parietal scalp locations [8-10] and it can also be used by patients suffering from complete paralysis and impairment in oculo-motor dysfunctions, such as locked-in patients.

It is notable, however, that 20% of subjects are not proficient in using BCI; this phenomenon is called “BCI illiteracy” [11] and it is due to the fact that some users do not produce brain activity detectable at the scalp level, independently from the health conditions: even about 10% of healthy subjects do not produce “usable” P300.

With regard to ALS patients, studies have shown that some of them produce less typical ERPs than healthy matched subjects [12]; [13]. A previous ERP study in patients with sporadic ALS found that P3a and P3b amplitudes of ALS patients were lower and P3a latencies were significantly longer compared with the controls [14]; ERP recordings in non-demented patients with sporadic ALS also showed prolonged N200 and P300 latencies compared to healthy controls [15]. Ogawa and colleagues [16], by employing neuropsychological measures, event-related potentials (ERP) and clinical scales, studied a sample of patients with early-stage sporadic ALS. They found that patients with the bulbar-onset type showed marked prolongation of P3 latency compared to patients with the limb-onset type and controls. Furthermore, bulbar functional rating scale correlated with prolonged P3 latency and low P3 amplitude. Additionally, patients with bulbar-onset ALS had consistently poorer cognitive test performance than those with limb-onset ALS [17]. These results may represent a challenge for the use of P300 as an input signal in BCIs. Kübler and Birbaumer [7] investigated the relationship between the level of motor and physical impairment and the ability to use brain computer interface by comparing three different BCI systems (P300, SCP – Slow Cortical Potentials and SMRs - sensorimotor rhythms). They found no continuous decrement in BCI performance with physical decline, even in the completed locked-in state (CLIS) where no communication was possible.

Two important criteria in order to evaluate the feasibility of a BCI system are speed and accuracy [18]. The former is related to the fact that the more rapidly a BCI can be controlled, the greater quantity of information can be produced by the user and the greater the chance for effective communication. Obviously, compared to verbal speech production, communication rate is severely reduced with BCI. With regard to accuracy, it consists of the percentage of correct selections per time interval. A wrong selection could turn into an error in communication, with both practical and psychological consequences for the user. In order to avoid this, the BCI system must be equipped with options that allow the user to correct wrong selections and a balance between speed and accuracy should be identified.

BCI has been preliminarily employed in order to administrate cognitive testing [33-35]. In a first study of Iversen and Colleagues [34], training was applied to two severely paralyzed ALS patients, during which the patients could learn to control certain components of their EEG in order to direct the movement of a visual symbol on a monitor. Following, a series of two-choice cognitive task were administered.

In a successive study, Iversen and Colleagues [35], employed the same SCP-EEG control in order to administrate a conditional-associative learning task to a late-stage ALS patient, testing the ability to learn arbitrary associations among visual stimuli. In both studies, a good level of accuracy was observed in detecting patients performances, according to a within subjects experimental design. Patients were also able to understand the verbal instructions and to respond accordingly in the successive tasks. However, this method owns some important limitation: first, it requires an extensive pretraining in order to learn to control EEG, which can take some weeks; second, the method cannot be used for tasks based on recall or where a choice must be made among more than two stimuli. Perego and Colleagues [33] adapted a widely used clinical test (Raven Colored Progressive Matrix) to a SSVEP-BCI paradigm in order to verify whether BCI affects the performance due to fatigue and cognitive load. They found, in a healthy population, that the BCI-based administration did not affect performance.

More recently, an innovative study [19] aimed to evaluate the complementary use of P300 BCI and eye-tracking technologies both as Augmentative and Alternative Communication (AAC) systems and as cognitive assessment tools.

The aim of this study is to develop an adapted computerized version of a widely used test for the assessment of executive functions, i.e. the Verbal Fluency test, to be administrated by means of BCI and ET devices. Moreover, we aimed to assess the overall system usability and user-friendliness. In order to fine-tune the overall testing setup, we performed a pilot study with 8 healthy subjects and one ALS patient. Specifically, participants were administrated a phonemic and semantic verbal fluency test; measures of feasibility, pleasantness and fatigue were also collected. Emotional aspects related to the experimental setting, have been evaluated, too. In this paper we report the results of this pilot study.

2. Materials and Methods

2.1. Participants

Eight healthy subjects (4 females and 4 males), aged between 25 and 39 (M: 31.75, SD: 5.946), were recruited. They were all volunteers with a schooling degree ranging from 13 to 24 years of education (M: 19, SD: 4.276). All the subjects were experienced in the use of PC (50% fair and good and 50% excellent), some of them (50%) declared to
have already used Brain Computer Interface or an Eye-tracker system, and more than half (62.5%) had already participated into EEG experiments. Exclusion criteria were the presence of cardiovascular, neurological, sensory or psychiatric diseases. Participants were asked to avoid drinking caffeine or alcohol and smoking prior to the experimental test in order to prevent any effects of these substances on the central and autonomic nervous system.

Besides, a male ALS patient with bulbar onset, (age: 46 years; years of education: 18), diagnosed by an expert consultant neurologist, according to the El Escorial Criteria (Brooks et al., 2000), was also included in the study. He was not experienced in the use of BCI or ET, while rated as good its experience in the use of PC. He has been recruited at the inpatient-outpatient Neuromuscular Clinic at the Department of Neurology of the San Luca Hospital, IRCCS Istituto Auxologico Italiano in Milan.

2.2. System Setting

Test architecture (Figure 1) was composed of an ET system and a BCI device, both controlled by a laptop PC, connected to an external monitor, meant for the stimuli presentation (Display PC). Figure 1 shows the adopted test setup. The BCI device module was based on the g.USBAmp (7) biosignal amplifier, connected to an active electrode head cuff (5). The biosignal amplifier was connected to a portable laptop (6). This laptop was connected to an external monitor (2), where the stimuli were presented to the participant. The ET consisted of a high-speed infrared camera and the related illuminator (3), positioned just below the Display Monitor. The ET host computer (1) acquired eye-head information via the camera and processed them in real time. The two computers were connected by Ethernet cross-cable, for fast communications in order to synchronize the different acquisitions performed by the BCI and the ET. This allowed to extract interesting features from the combined use of both technologies, e.g. the screen eye-gaze patterns during the BCI tests.

On the Display PC a suitable custom software provided information of the general management of the tests and the sequence of the stimuli for the ET tests, while for the BCI, we used an adapted version of the widespread used BCI2000.

![Figure 1. Setup Example: (1) Eye-tracker Host Computer, (2) Eye-tracker Display Monitor, (3) Eye-tracker sensing device, (4) User, (5) EEG Head Cuff, (6) Display PC, (7) EEG Amplifier, (8) Operator](image)

**Brain Computer Interface**

For BCI, a g.USBamp amplifier has been used (Guger Technologies, Graz, Austria), connected to an active electrodes head cuff (g.GammaCap, Guger Technologies). It was enabled with 16 simultaneously sampled biosignal channels with 24-bit resolution with simultaneous sampling of all channels with up to 38.4 kHz, and digital signal filtering and preprocessing with active electrodes. Independent grounds guaranteed no interference between the recorded signals. Input voltage ranged +/- 250 mV with a resolution of less than 30 nV. Moreover, a floating point DSP performed oversampling and real-time filtering of the signal data (between 0 Hz and 2,400 Hz).

The systems came as CE-certified and FDA-approved medical device, safety class: II, conformity class: Ila, type of applied part: CF.

To setup the BCI system we used a g.USBamp amplifier for the acquisition of 16 EEG channels. Channel names based on the International 10-20 locations were: FZ, C3, C4, CZ, CPZ, P3, P4, PZ, PO3, PO4, POZ, PO7, PO8, O1, O2, OZ; ground was placed in FPZ, and reference was located on the left ear lobe.

**Eye-tracking**

The ET was an Eyelink-1000 (SR Research Ltd., Mississauga, Ontario, Canada), consisting of a high-speed infrared camera and the related illuminator, positioned just below the Display Monitor.

Eye movement data consisted of moment-to-moment measures of the eyes’ displacements along the vertical and horizontal axes (in millimeters) within the spatial working area of the monitor screen.

The pupil dilation and gazes were acquired, based on the pupil position and the corneal reflection on the frontal surface of participants’ eyes (caused by an infrared light source), at 500 Hz (one record data per 2 milliseconds) by means of a EyeLink 1000 using custom software programmed in C. After the experiment, the signals were
Subjects were asked to copy a list of words, using two different kinds of keyboards. The first one was a standard keyboard, with letters arranged in alphabetical order (from A to Z), while the second one was a "scrambled" keyboard, with letters arranged in random order (Fig 3). Execution times taken for both tasks were recorded. The aim of this test was to assess the user facilitation for the standard keyboard due to the reduced visual searching effort in comparison with the random arranged letters.

2.5. Psychological Self-reportQuestionnaires

STAI form Y Questionnaire
The Italian version of the STAI form Y questionnaire was used to assess changes in two different types of anxiety, namely, anxiety detected as the subject's current state (STAI-Y1, i.e. state anxiety) and anxiety detected as a reasonably stable trait of the personality of an individual (STAI-Y2, i.e., trait anxiety). A total of four Self-reported STAI-Y1 were gathered before and after both BCI and Eye-tracking sessions. One self-reported STAI-Y2 was gathered five minutes before the experimental session.

Self Assessment Manikin (SAM)
One of the most currently employed methods for identifying affective states in subjects during an experimental session is the Self Assessment Manikin (SAM). It is a non-verbal pictorial assessment technique that considers the two dimensions of "activation", namely, physiological arousal and emotional valence and directly measures the pleasure, arousal, and dominance associated with subjects' affective reactions. A total of four Self-reported SAMs were gathered before and after both BCI and ET sessions.

2.6. Usability Inventory Post-test Questionnaire

Since there are no usability validated tests for ET and BCI systems, we developed a questionnaire composed of 19 items, based on the available literature. Our purpose was to evaluate the instruments' general usability and some specific variables such as fatigue, screen readability and perceived usefulness.

2.7. Experimental Procedures

Experiments were performed at the Applied Technology for Neuro-Psychology Laboratory and at the San Luca Hospital, both located at the IRCCS Istituto Auxologico Italiano in Milan. Participants were tested by a neuropsychologist and a senior psychology researcher.

The experimenters were instructed to maintain a neutral vocal tone and a neutral behavior for the entire duration of the experimental session.
3. Results

Data were analyzed with the aid of the statistical software SPSS, version 17 (Statistical Package for the Social Sciences–SPSS for Windows, Chicago, Illinois, USA). Nonparametric tests were preferred, even if several measures showed a normal distribution (according to Kolmogorov-Smirnov test). In the following paragraphs the main results of this preliminary study are presented.

3.1. Fluency Tests

In BCI session, Phonemic Verbal Fluency average time was 6.42±2.76 seconds and Semantic Verbal Fluency average time was 4.08±1.94 seconds. Regarding the ET session, we used the Fluency Index, as above described. Phonemic Verbal Fluency Index was 4.28±5.84 seconds and the Semantic Verbal Fluency Index was 3.37±2.58 seconds. These data will be used to compare future patients’ performances.

3.2. Behavioral Measures

In order to assess if BCI and ET generated negative affective states, anxiety level has been first measured via the STAI-Y1 questionnaire for the two different conditions on BCI (pre- and post-BCI), and the two different conditions on ET (pre- and post-ET). Measures of pre-post ET and BCI were also collected for the three scales of the SAM questionnaire, namely pleasure, arousal, and dominance. Wilcoxon Signed Ranks Tests indicated no statistical differences for both the pre-post STAI-Y1 and pre-post SAM scales, indicating that no negative affective state or anxiety have been generated by the performance with BCI or ET. However, a small increase in anxiety was detected after the use of BCI.

3.3. Usability

As it is showed in Table 1, subjects recognized both systems as enough usable, but ET was generally perceived as more usable than BCI (statistical significance is calculated with Wilcoxon Signed Ranks Tests). To analyze the answers to items which emphasize a positive impact of the instruments (item: 1, 2, 4, 5, 6, 10, 11, 12, 14, 18, and 19), a model of internal consistency, based on the average inter-item correlation, showed Cronbach’s Alphas of 0.792 and 0.784, respectively for BCI and ET. The average value of the "positive item" consequently created allowed us to compare BCI and ET (5.17±0.96 vs. 6.06±0.53; Z = -2.66, p = .008), and to confirm the highest perceived usability for the ET system, also considering only positive items.

Table 1. Average values of 7-point Likert scale items of the usability questionnaire

<table>
<thead>
<tr>
<th>ID</th>
<th>Item</th>
<th>Mean BCI</th>
<th>Mean ET</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>It is easy to use the</td>
<td>5.25</td>
<td>6.25</td>
<td>.131</td>
</tr>
<tr>
<td></td>
<td>device</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>The instructions are</td>
<td>6.25</td>
<td>6.50</td>
<td>.157</td>
</tr>
<tr>
<td></td>
<td>clear</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Sometimes I wondered if</td>
<td>2.25</td>
<td>1.75</td>
<td>.336</td>
</tr>
<tr>
<td></td>
<td>I was selecting the right</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
3.4. Copying Text using Different Keyboards with Eye-tracking

The mean time to copy a list of words with the standard virtual keyboard (in alphabetic order, since QWERTY layout wasn’t familiar to all participants) was 46.09±6.55, while the average time to copy the same text with the scrambled keyboard was 60.17±21.23. Wilcoxon Signed Ranks Tests indicated statistical significant differences (Z = -2.201, p = .028).

3.5 BCI Calibration

BCI calibration is a critical issue. Above all, it is crucial to verify if such process affects BCI results, in terms of errors made during the experimental test. In the healthy sample, the mean calibration accuracy was 89.73%, while the accuracy of BCI system during the test was 81.72% (i.e. 18.28% of errors). However, since 6 subjects obtained 100% of correct calibration and did very few errors, we were interested in understanding if such two processes (calibration and final results) was correlated. Results showed a negative Spearman's correlation (\( \rho = -0.862, p = .028 \)), indicating that good calibration seems to lead to fewer errors.

3.6 Case study

In order to preliminarily evaluate the feasibility of BCI and ET systems for cognitive assessment and communication purposes also in a clinical population, we collected data from one ALS patient (M.Z.). Main results are shown in Tables 2 and 3. With regard to BCI, data suggested a level of accuracy in calibration and testing, which is comparable to that obtained by healthy subjects.

Concerning ET, the overall performance supported a good rate of accuracy. Moreover, no relevant differences in STAI and SAM pre and post BCI and ET scores were recorded.

<table>
<thead>
<tr>
<th>Test</th>
<th>Result</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>BCI</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>STAI Y1 Pre BCI</td>
<td>45</td>
<td></td>
<td></td>
</tr>
<tr>
<td>STAI Y1 Post BCI</td>
<td>48</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 3. The used ET Keyboards and the Saccades plotted over them: (a) Standard Virtual Keyboard, (b) Scrambled Keyboard, (c) Saccades on Standard Virtual Keyboard, (d) Saccades on Scrambled Keyboard.
Cognitive Assessment of Executive Functions using Brain Computer Interface and Eye-tracking

| SAM Pre BCI | P: 3; A: 2; D: 4 |
| SAM Post BCI | P: 3; A: 2; D: 4 |
| Err. PVF | 0/27 |
| Err. SVF | 0/27 |

ET

| STAI Y1 Pre ET | 48 |
| STAI Y1 Post ET | 50 |
| SAM Pre ET | P: 3; A: 2; D: 3 |
| SAM Post ET | P: 3; A: 2; D: 3 |
| Time PVF Gen. | 120 Sec. |
| Time PVF Copy | 84.7 Sec. |
| Time SVF Gen. | 120 Sec. |
| Time SVF Copy | 101.2 Sec. |
| Err. PVF Gen. | 15707 |
| Err. PVF Copy | 0/43 |
| Err. SVF Gen. | 0/61 |
| Err. SVF Copy | 2288 |

SAM: P (Pleasure), A (arousal), D (dominance);
PVE: Phonemic Verbal Fluency;
SVF: Semantic Verbal Fluency; Gen.: Generation

Table 3. ALS patient scores on ET and BCI usability questionnaire

<table>
<thead>
<tr>
<th>BCI</th>
<th>It.1</th>
<th>It.2</th>
<th>It.3</th>
<th>It.4</th>
<th>It.5</th>
<th>It.6</th>
<th>It.7</th>
<th>It.8</th>
<th>It.9</th>
<th>It.10</th>
<th>It.11</th>
<th>It.12</th>
<th>It.13</th>
<th>It.14</th>
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<td>2</td>
<td>6</td>
<td>6</td>
<td>7</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>6</td>
<td>2</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ET</th>
<th>It.1</th>
<th>It.2</th>
<th>It.3</th>
<th>It.4</th>
<th>It.5</th>
<th>It.6</th>
<th>It.7</th>
<th>It.8</th>
<th>It.9</th>
<th>It.10</th>
<th>It.11</th>
<th>It.12</th>
<th>It.13</th>
<th>It.14</th>
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<th>It.16</th>
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<td>2</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>6</td>
</tr>
</tbody>
</table>

4. Conclusions and Future Work

No studies have been performed so far to evaluate the combined use of BCI and ET system for AAC and cognitive assessment in ALS.

As previously mentioned, BCI is a system that enables the generation of a control signal from brain responses such as sensorimotor rhythms and evoked potentials; it bypasses motor output and conveys messages directly from the brain to a computer. Therefore, it constitutes a novel communication option for people with severe motor disabilities, such as ALS patients. Another available technology for communication purposes is the ET system.

Starting from these considerations, a comprehensive neuropsychological battery based on the use of P300-based BCI and Eye-tracker could be created. In particular, some traditional neuropsychological tests could be modified to create computerized short versions of several tests, that could be adapted for BCI and ET administration.

Our pilot study provided evidences for the effectiveness and usability of these techniques. Specifically, the BCI computerized assessment could provide new insights into the understanding of cognitive deficits, when administered to ALS patients, through the integration of multidisciplinary data: neurophysiological, neuropsychological, behavioural and psychological.

The proposed study is characterized by at least two innovative aspects: (1) the comparison between two interesting technologies, one already extensively investigated (ET), the other being a very promising candidate (P300-based BCI), (2) the adaptation to BCI and ET of the Verbal Fluency task for the neuropsychological assessment of higher order cognitive functions in ALS patients. As we described above, some preliminary attempts have been made in this direction [33-35]. However, the known adopted BCI paradigms require non trivial adjustments of the original neuropsychological test procedures and a training phase before tests administration. Differently, in P300-based BCIs here employed the learning of self-regulation of the brain response and feedback is not necessary and the short latency of the P300 allows a selection of items faster than any other BCI systems.

Results showed a good usability of both instruments, better for ET, but promising for BCI too. Furthermore, the strong negative correlation between trait anxiety and perceived usability clearly showed that the higher the subject is anxious, the more the instruments will be perceived as demanding, tiring, and difficult to use.

Finally, no emotional effects on cognitive performances were revealed by the administered psychological measures.

As expected, BCI calibration was a critical issue. These data suggested that it is crucial to extend the calibration phase in order to reach very high correct ratio (close to 100%). Moreover, the kind of virtual keyboard used in the task clearly influences the observed performances. This result suggest a potential use of the scrambled keyboard as a novel cognitive test.

Finally, these preliminary results may have interesting implications for both clinical practice (the availability of an effective tool for neuropsychological evaluation of ALS patients) and ethical issues, the last one arising from a proper assessment of cognitive ability preservation, in particular regarding relevant decisions about medical treatments, economical and end-life issues.

Acknowledgements.

This study has been made possible partially due to funds from the Lombardy Region project "eBrain: BCI-ET for ALS (eBrain: BCI-ET nella SLA)". A preliminary version of this work has been presented at MindCare Workshop and published in [32]. This new version contains a renewed "materials and methods" section to better explain the complex technologies used in the
study. More, results have been enriched by adding new analysis and a renewed discussion has been written accordingly.

References


Computerized experience-sampling approach for real-time assessment of stress

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3Department of Psychology, Catholic University of Milan, Italy

Abstract

The incredible advancement in the ICT sector has challenged technology developers, designers, and psychologists to reflect on how to develop technologies to promote mental health. Computerized experience-sampling method appears to be a promising assessment approach to investigate the real-time fluctuation of experience in daily life in order to detect stressful events. At this purpose, we developed PsychLog (http://psychlog.com) a free open-source mobile experience sampling platform that allows psychophysiological data to be collected, aggregated, visualized and collated into reports. Results showed a good classification of relaxing and stressful events, defining the two groups with psychological analysis and verifying the discrimination with physiological measures. Within the paradigm of Positive Technology, our innovative approach offers for researchers and clinicians new effective opportunities for the assessment and treatment of the psychological stress in daily situations.

Keywords: experience-sampling method, pervasive computing, psychological stress, psychophysiology, heart rate variability.

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1. Introduction

The incredible enhancements in the field of Information and Communication Technologies (ICTs) are dramatically affecting our daily individual and social life. Nowadays, the technological progress has enabled the development of devices that are not only increasingly sophisticated, but also low-cost and user-friendly. As recently suggested by Riva and Colleagues [1], the advancement in the ICT sector has challenged technology developers, designers, and psychologists to reflect on how to develop technologies to promote mental health. In this perspective, Positive Psychology appears to be a promising framework to develop ICTs that foster positive emotions, promote engagement in empowering activities and support connectedness between individuals, groups, and communities to social and cultural development. Indeed, Positive Psychology is the scientific study of well-being to understand human strength and virtues and to promote them to allow individuals, communities, and societies to thrive [2-6]. This progressive convergence between the objectives of Positive Psychology with enhancements of ICTs has led toward a new paradigm, namely Positive Technology. Positive Technology is an emerging discipline that could be defined as the scientific and applied approach to the use of advanced technology for improving the quality of our personal experience [1,7]. Within this framework, self-tracking appears to be a fast-growing trend in the field of e-health that consists in the “regular collection of any data that can be measured about the self such as biological, physical, behavioral or environmental information. Additional aspects may include the graphical display of the data and a feedback loop of introspections and self-experimentation” [8]. This approach is enabled by the fecund convergence between ICTs and wearable biosensors, which allow personal health data to be collected, aggregated, visualized, collated into reports and
shared [9]. Self-tracking is rooted into the experience sampling approach, originally a paper-and-pencil methodology developed by Csikszentmihalyi and Larson [10]. As underlined by Ebner-Priemer and Trull [11], different terms have been used to refer to real-time assessment of psychophysiological data: Ambulatory Assessment [12-14], Ecological Momentary Assessment [15], Experience Sampling Method [16], Real-Time Data Capture [17], and Day Reconstruction Method [18]. These assessment methodologies, although arising from different research paradigms, have in common the continuous recording of psychological and physiological data or indices of behavior, cognition or emotions in the daily life of individuals. Barrett and Barrett [19] effectively defined real-time assessment procedure as a “window into a daily life” since participants provide self-reports of their momentary thoughts, feelings and behavior across a wide range of daily situations in ecological contexts. This approach appears particularly promising for the assessment of psychological stress. Assessing and monitoring emotional, cognitive and behavioral dimensions of human experience, both in laboratory and in natural setting, in fact, have a crucial role in the research and treatment of psychological stress.

According to Cohen and Colleagues [20], “Psychological Stress” occurs when an individual perceives that environmental demands tax his/her adaptive capacity. In this perspective, stressful daily experiences could be conceptualized as a continuous person-environment transaction [21,22]. Every day, in fact, individuals are continually invited to deal with several situations or circumstances (for example, being fired from work or having trouble with parents or partner) that provoke anxiety and psychological discomfort. In this perspective [20-22], a stressful event [23,24] occurs when a person isn’t able to effectively cope with a challenge that is perceived to exceed his/her skills. Physiological measures can also give further information to a psychological definition of stress, but there are still few studies, above all in everyday situations, considering the relation between these two dimensions.

To accurately analyze real-time interaction between environmental demands and individual adaptive capacity and to precisely detect stressful events during the daily life situations, it is fundamental to use a real-time multimodal assessment.

As above described, recent progress in biosensor technology and, on the other hand, the incredible diffusion of ICTs have led to ubiquitous and unobtrusive recorder systems that allow naturalistic and multimodal assessment [9,19,25-27].

Computerized experience sampling method comprising a mobile-based system that collects psychophysiological data appears to be a very promising assessment approach to investigate the real-time fluctuation of experience in everyday life in order to detect stressful events.

At this purpose, we developed PsychLog (http://psychlog.com) a free open-source mobile experience sampling platform that allows psychophysiological data to be collected, aggregated, visualized and collated into reports [28,29]. Our mobile-based system collects physiological data from a wireless wearable electrocardiogram equipped with a three-axial accelerometer. Moreover, the application allows administering self-report questionnaires [30] to collect and investigate participants’ feedback on their daily experience in its various cognitive, affective and motivational dimensions.

In this study, we proposed and tested the use of PsychLog to investigate the fluctuation of experience during a week of observation and to detect, on the basis of psychophysiological real-time assessment, both stressful and relaxing events that normally occur during daily activities in ecological contexts.

![Figure 1. PsychLog: The sensing computing and visualization modules](image-url)
2. Materials and methods

2.1. Participants

Participants were six healthy subjects (2 males and 4 females, mean age 23) recruited through opportunistic sampling. Participants filled a questionnaire assessing factors that might interfere with the psychophysiological measures being assessed (i.e., caffeine consumption, smoking, alcohol consumption, exercise, hours of sleep, disease states, medications). Written informed consent was obtained by all participants matching inclusion criteria (age between 18-65 years, generally healthy, absence of major medical conditions, completion of informed consent).

2.2. Tools

In our study we used PsychLog (http://psychlog.com), a mobile experience sampling platform that allows the collection of psychological, physiological and activity information in naturalistic settings [28,29]. The system consists of three main modules.

The survey manager module allows configuring, managing and administering self-report questionnaires. Triggers can be launched with a fixed schedule or randomly during a day.

The sensing/computing module allows continuously monitoring heart rate and activity data acquired from a wireless electrocardiogram (ECG) equipped with a three-axis accelerometer. The wearable sensor platform (Shimmer Research™) includes a board that allows the transduction, the amplification and the pre-processing of raw sensor signals, and a Bluetooth transmitter to wirelessly send the processed data. Sensed data are transmitted to the mobile phone Bluetooth receiver and gathered by the PsychLog computing module, which stores and process the signals for the extraction of relevant features. ECG and accelerometer sampling intervals (epochs) can be fully tailored to the study’s design.

During each epoch, signals are sampled at 250 Hz and filtered to eliminate common noise sources using Notch filter at 0 Hz and low pass at 35 Hz and analogue-to-digital converted with 12-bit resolution in the ±3 V range. The application extracts QRS peaks through a dedicated algorithm and R-R intervals [31,32]. These intervals are then transformed to a tachogram, i.e., the series of R-R intervals durations as a function of the interval number.

The visualization module allows plotting in real time ECG and acceleration graphs on the mobile phone’s screen. This feature is useful either for monitoring the ECG data or for checking the functioning of the ECG sensor apparatus.

Psychological and physiological data are stored on the mobile phone’s internal memory, in separate files, for offline analysis. Data are stored as .dat (supported by most data analysis programs), .txt and .csv format.

In this study, we used standard smartphone (Samsung Omnia II i8000) equipped with 32 bit CPU, ARM 11 RISC processor (cache 16KB) 667 MHz, RAM 256 MB, 1500 mAh Lithium ion battery, running the operative system Windows mobile 6.5. PsychLog platform implementation, architecture, and technical aspects were discussed further in a previous research [33].

2.3. Procedure

Participants were provided with a short briefing about the goal of the experiment and filled the informed consent. Then, they were provided with the mobile phone with pre-installed PsychLog application, the wearable ECG and accelerometer sensor and a user manual including experimental instructions. Subjects were asked to wear biosensor for one week of observation. PsychLog was pre-programmed to beep randomly 5 times a day each day (between 10 AM and 10 PM) to elicit at least 35 experience samples over the 7-days assessment period. At the end of the experiment, participants returned both the phone and the sensors to the laboratory staff. After filling a short usability questionnaire, participants were debriefed and thanked for their participation.

2.4. Psychological Assessment

Psychological stress was measured by using a digitalized version of an ESM survey adapted from that used by Jacobs and Colleagues [28,30] for studying the immediate effects of stressors on mood. The self-assessment questionnaire included open-ended and closed-ended questions (rated on 7-point Likert scales) investigating thoughts, current context (activity, people, location, etc.), appraisals of the ongoing situation, and mood. Following the procedure suggested by Jacobs and Colleagues [30], three different scales were computed in order to identify the stressful qualities of daily experiences. Ongoing Activity-Related Stress (ARS) was defined as the mean score of the two items “I would rather be doing something else” and “This activity requires effort” (Cronbach’s alpha = 0.699). To evaluate social stress, participants rated the social context on two 7-point Likert scales “I don’t like the present company” and “I would rather be alone”; the Social Stress scale (SS) resulted from the mean of these ratings (Cronbach’s alpha = 0.497). For Event-Related Stress (ERS), subjects reported the most important event that had happened since the previous beep. Participants then rated this event on a 7-point scale (from 0 very unpleasant to 3 very pleasant, with 0 indicating a neutral event). All positive responses were coded as 0, and the negative responses were coded so that higher scores were associated with more unpleasant and potentially stressful events (0 neutral, 3 very unpleasant).
In addition to those scales (not included in the original survey), we introduced an item asking participants to rate the perceived level of stress (STRESS) on a 10-point Likert scale. In particular, to rate the gap between challenge and skills, we used two specific items: (1) an item assessing the perceived level of ongoing challenge (CHALLENGE) on 7-point Likert; (2) an item evaluating the perceived level of skills (SKILLS) on 7-point Likert.

2.5. Activity

ECG biosensors used by PsychLog application has also an integrated three-axial accelerometer.

This accelerometer permits the computation of activity indexes used to establish the macro movements of a subject during the recording of ECG. It is useful, for example, to avoid to detect signals when he/she is running.

\[ \text{SMA} = \sum_{i=1}^{n} (|x(i)| + |y(i)| + |z(i)|). \]  

where x(i), y(i), and z(i) indicate the acceleration signal along the x-axis, y-axis, and z-axis, respectively.

2.6. Cardiovascular indexes

Cardiovascular activity is monitored to evaluate both voluntary and autonomic effect of respiration on heart rate, analyzing R-R interval from electrocardiogram. Furthermore standard HRV spectral methods indexes and similar have been used to evaluate the autonomic nervous system response [36].

From ECG each QRS complex is detected, and the normal-to-normal (NN) intervals (all intervals between adjacent QRS complexes resulting from sinus node depolarisations) are determined to derive the most common temporal measures, including RMSSD, the square root of the mean squared differences of successive NN intervals, and NN50, the number of interval differences of successive NN intervals greater than 50 ms [36]. In general, RMSSD are estimate of short-term components of heart rate variability.

This experiment aimed at testing the feasibility of monitoring concurrent stress and physiological arousal within subjects’ typical daily environments and activities. Previous works have shown that psychological stress is associated with an increase in sympathetic cardiac control, a decrease in parasympathetic control, or both [31,32]. Associated with these reactions is a frequently reported increase in low frequency (LF, range between 0.04-0.15 Hz) or very low frequency (VLF, < 0.04 Hz) HRV, and decrease in high frequency (HF, 0.15–0.50 Hz) power. HF power is reported to reflect parasympathetic modulation of RR intervals related to respiration, whereas the LF component is an index of modulation of RR intervals by sympathetic and parasympathetic activity (in particular baroreflex activity) [31,32,36]. Furthermore, stressors are often accompanied by an increase in the LF/HF ratio (a measure used to estimate sympathovagal balance, which is the autonomic state resulting from the sympathetic and parasympathetic influences) [36].

Although the time domain methods, especially RMSSD method, can be used to investigate recordings of short durations, the frequency methods are usually able to provide results that are more easily interpretable in terms of physiological regulations [36].

Spectral analysis has been performed by means of autoregressive (AR) spectral methods with custom software. The AR spectral decomposition procedure has been applied to calculate the power of the oscillations embedded in the series.

The rhythms have been classified as very low frequency (VLF, <0.04 Hz), low-frequency (LF, from 0.04 to 0.15 Hz) and high frequency (HF, from 0.15 to 0.5 Hz) oscillations.
The power has been expressed in absolute (LF_{RR} and HF_{RR}) and in normalized units. For example RR series: LF_{nu} and HF_{nu} as 100 \times \frac{LF_{RR}}{\sigma^2_{RR}} \, VLF_{RR} and 100 \times \frac{HF_{RR}}{\sigma^2_{RR} - VLF_{RR}}, where \sigma^2_{RR} represents the RR variance and VLF_{RR} represents the VLF power expressed in absolute units [31,32,36].

3. Data analysis

In order to detect both stressful and relaxing events, Activity-Related Stress Scale (ARS), Social Stress Scale (SS), Perceived Stress Scale (STRESS), Challenge Scale (CHALLENGE) and Skill Scale (SKILLS) were within-subjects standardized. Event-Related Stress Scale wasn’t standardized so it was classified as follows: 0 = no stress; 1 = low stress; 2 = medium stress; 3 = high stress.

We proposed the classification in Table 1 to define stressful and relaxing events.

<table>
<thead>
<tr>
<th>Event</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>STRESS</td>
<td></td>
</tr>
<tr>
<td>Zscore(STRESS)</td>
<td>&gt; 1</td>
</tr>
<tr>
<td>Zscore(ARS)</td>
<td>&gt; 1</td>
</tr>
<tr>
<td>Zscore(SS)</td>
<td>&gt; 1</td>
</tr>
<tr>
<td>ERS</td>
<td>&gt; 1</td>
</tr>
<tr>
<td>Zscore(CHALLENGE) &amp; Zscore(SKILLS)</td>
<td>&gt; 1 &amp; &lt; - 1</td>
</tr>
<tr>
<td>RELAX</td>
<td></td>
</tr>
<tr>
<td>Zscore(STRESS)</td>
<td>&lt; - 1</td>
</tr>
<tr>
<td>Zscore(ARS)</td>
<td>&lt; - 1</td>
</tr>
<tr>
<td>Zscore(SS)</td>
<td>&lt; - 1</td>
</tr>
<tr>
<td>ERS</td>
<td>= 0</td>
</tr>
<tr>
<td>Zscore(CHALLENGE) &amp; Zscore(SKILLS)</td>
<td>&lt; - 1 &amp; &gt; 1</td>
</tr>
</tbody>
</table>

Hierarchical structure of the experiment data makes traditional forms of analysis unsuitable. Subjects are measured at many time points during each day, across seven days. Traditional repeated-measures designs require the same number of observations for each subject and no missing data. Multilevel models are appropriate to analyze such data above all because the existent dependencies due to repeated measurements are included in the parameter estimates. Moreover, also other dependencies existing in the data can be taken into account.

Because the ESM entries are nested within seven days within participants, we estimated the psychophysiological indexes on events (Relax or Stress), with hierarchical linear analysis, an alternative to multiple regression suitable for our nested data. We referred to two levels in the model: beep-level and subject-level. Our model was based on binary logistic, specifying Binomial as the distribution and Logit \( f(x) = \log(x / (1-x)) \) as the link function.

Using a mixed hierarchical model we inferred the dichotomised event (Relax or Stress) on the basis of physiological parameters. In this sense we used these indexes to predict relax or stress condition indicated by subjects. The analysis aimed at finding statistically significant parameter for the estimation of a model designed to predict relaxing and stressful events. More, a linear discriminant analysis (LDA) has been used to verify if a set of physiological measures (RMSSD, NN50, and HF Power) was able to discriminate between the two groups (Relax and Stress).

4. Results

The six participants completed a total of 213 ESM reports. Aggregated over participants’ means, mean Perceived Stress was 2.99 (S.D. = 1.50), mean Activity-Related Stress was 3.35 (S.D. = 0.72), mean Social Stress was 3.34 (S.D. = 1.40), mean Challenge was 2.99 (S.D. = 1.92), mean Skills was 4.58 (S.D. = 1.86), and frequencies for Event-Related Stress was: 88% no stress, 4.2% low stress, 3.1% medium stress, and 4.7% high stress.

A total of 31 events (14.55 % of total events) have been identified, 18 relax events (8.45 %) and 13 stress events (6.10 %) among the six subjects. For each one of these events we calculated two temporal HRV indexes, namely RMSSD and NN50, and one spectral HRV index, i.e. HF power.

A linear discriminant analysis (LDA) has been used to verify if the physiological indexes (RMSSD, NN50, and HF Power) were able to discriminate between the two groups (Relax and Stress) defined on the basis of the questionnaires, as above defined. Tests of equality of group means are showed in table 3. More, results showed a 0.622 Wilks’ Lambda (Chi-square: 13.070, df: 3, p < .005) with 77.4% of original grouped cases correctly classified (see table 4).
Table 2. Group Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Valid N (listwise)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RELAX</td>
<td>Zscore(RMSSD)</td>
<td>.2175527</td>
<td>.78903922</td>
</tr>
<tr>
<td></td>
<td>Zscore(NN50)</td>
<td>.3686125</td>
<td>.80597461</td>
</tr>
<tr>
<td></td>
<td>Zscore(HF_pwr)</td>
<td>.4263368</td>
<td>.81428263</td>
</tr>
<tr>
<td>STRESS</td>
<td>Zscore(RMSSD)</td>
<td>-.4225023</td>
<td>.73893069</td>
</tr>
<tr>
<td></td>
<td>Zscore(NN50)</td>
<td>-.5293378</td>
<td>.62354657</td>
</tr>
<tr>
<td></td>
<td>Zscore(HF_pwr)</td>
<td>-.5657602</td>
<td>.57913531</td>
</tr>
</tbody>
</table>

Table 3. Tests of equality of group means

<table>
<thead>
<tr>
<th></th>
<th>Wilks' Lambda</th>
<th>F</th>
<th>df1</th>
<th>df2</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zscore(RMSSD)</td>
<td>0.847</td>
<td>5.233</td>
<td>1</td>
<td>29</td>
<td>0.03</td>
</tr>
<tr>
<td>Zscore(NN50)</td>
<td>0.721</td>
<td>11.236</td>
<td>1</td>
<td>29</td>
<td>0.002</td>
</tr>
<tr>
<td>Zscore(HF_pwr)</td>
<td>0.673</td>
<td>14.085</td>
<td>1</td>
<td>29</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Table 4. Classification Results. Overall, 77.4% of original grouped cases correctly classified

<table>
<thead>
<tr>
<th></th>
<th>Predicted Group Membership</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition</td>
<td>Relax</td>
<td>Stress</td>
</tr>
<tr>
<td>Original Relax</td>
<td>72.2 %</td>
<td>27.8 %</td>
</tr>
<tr>
<td>Original Stress</td>
<td>15.4 %</td>
<td>84.6 %</td>
</tr>
</tbody>
</table>

As explained in data analysis, because the ESM entries are nested within seven days within participants, we estimated the psychophysiological indexes on events (Relax or Stress), with hierarchical logistic analysis, an alternative to multiple logistic regression suitable for our nested data. Results show, a statistical significant hierarchical regression model for RMSSD (Beta: 1.177; St. Dev.: .5839; p < .044), and a quasi statistical significant for HF power (Beta: .888; St. Dev.: .4612; p < .055). The RMSSD method is preferred to NN50 because it has better statistical properties [36].

5. Discussions and Conclusion

Recent progress in the sophistication and feasibility of biosensor technology and the remarkable spread of ICTs have led to ubiquitous and unobtrusive recorder systems that allow naturalistic and multimodal assessment of psychophysiological parameters [19,25,26]. Computerized experience sampling method comprising a mobile-based system that collects psychophysiological data seems to be a very promising assessment approach to investigate the real-time fluctuation of the quality of experience in daily contexts. Since psychological stress could be defined as a continuous person-environment transaction [20-22], this integrated and mobile assessment offers the opportunity to analyze the real-time interaction between challenges and skills occurring in daily life situations.

In this study, we proposed and tested the use of PsychLog [28] (http://psychlog.com) a free open-source mobile experience sampling platform, aggregated, visualized and collated into reports, to investigate the fluctuation of individual’ experience [16,29] and to detect, on the basis of psychophysiological real-time assessment, stressful events that normally occur during daily activities and situations.

Analysis has been set selecting two events groups (Relax and Stress) on the basis of psychological questionnaires. Then, an hierarchical logistic analysis, an alternative to multiple logistic regression suitable for our nested data and a discriminant analysis between the two groups, showed that physiological measures have been able to predict the groups selected on psychological basis. These results seem to indicate that a relation between physiological patterns and psychological behavior exists. Being true these results, we would be able to predict particular events on physiological basis, i.e. without having to ask subjects about their own states.

Within the paradigm of Positive Technology, our innovative approach offers for researchers and clinicians new effective opportunities for the assessment and treatment of psychological stress in daily environments.

The advantages in using a mobile psychophysiological stress assessment are potentially several: (a) it is possible to evaluate the continuous fluctuation of the quality of experience in ecological contexts; (b) it is possible to schedule the timing and the modality of psychophysiological monitoring; (c) it allows a multimodal assessment, comprising psychological, physiological, behavioral and contextual data; (d) it permits the detection of stressful events in daily life; and (e) it provides the opportunity of giving immediate, graphical and user-friendly feedback. In this perspective, a mobile self-tracking could be conceived as a persuasive technology [37] that allows individuals to accurately monitor their mental health and check their progress with...
encouraging and motivating feedback enhancing self-efficacy [38].

Finally, as a consequence of the detection of a stressful event, PsychLog may offer the chance to deliver real-time and effective Ecological Momentary Interventions [39-41] or a mobile biofeedback training [27,42] to provide real-time support for mental health in the natural context, when it is most needed. In conclusion, as for any new tools, much more research is necessary to evaluate our approach.

Acknowledgements.
The present work was supported by the European funded project “Interstress – Interreality in the management and treatment of stress-related disorders” (FP7- 247685). A preliminary version of this work has been presented at MindCare Workshop and published in [43]. This version contains a renewed introduction to better explain the Positive Technology paradigm within which this study has been carried out. More, a deeper data discussion and explanation of biosensors has been given accordingly.

References
Mental Health Research. Personal and Ubiquitous Computing.


Special Issue on “Technology for Mental Health”

Call for Papers

Technological advancements have been substantially influencing medical sciences, enabling their accelerated development. The goal is to advance the knowledge about health problems, improve diagnosis and afford higher quality of life for people. For mental disorders this afforded a number of benefits related to the continuous state assessment, evaluation of the effectiveness of therapy and medication, self-treatment support and much more. In addition, pervasive computing solutions can provide new concepts in supporting patients to maintain or regain a healthy mental state. According to the World Health Organization (WHO), mental disorders have a major negative impact on economy and on the quality of life of individuals and their families. Apart from the treatment, special emphasis should be put on the prevention of healthy subjects aiming to their cognitive well-being.

This special issue focuses on the exploitation of technology in favor of cognitive and emotional well-being, including, but not limited to, the following topics:

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- Innovative interventions for improving depressive behavior
- Technological tools as a support for individuals exposed to high levels of stress
- Investigating the influence of environmental factors on emotional status
- Unobtrusive tracking of long-term cognitive changes
- Automatic mood recognition
- Employing Bio and Activity sensors to monitor mental health
- Virtual reality approaches for therapy
- Biofeedback in stress management

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Manuscripts due: April 30, 2012
Acceptance Notification: June 8, 2012
Final manuscripts due: June 20, 2012

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