AMISIA: A multidisciplinary approach for the secondary prevention of the loss of autonomy for patients with traumatic brain injury and stroke

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Extended Abstract: AMISIA: A multidisciplinary approach for the secondary prevention of the loss of autonomy for patients with traumatic brain injury and stroke

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Abstract - AMISIA a multidisciplinary, 36 months Defi CNRS AUTON project, aimed at the secondary prevention of the loss of autonomy for patients with traumatic brain injury and stroke. As "any patient is a unique case," AMISIA proposes an integrated approach, mixing medical health devices, information technology, and human factors to provide patients, health care actors and caregivers from the relatives both the best incentives and high degree of monitoring.

This first step aims to define a methodology to determine the indicators necessary to promote physical activity in traumatic brain injury and stroke patient. In line with the primary aim, we conducted a data collection experiment in Limoges with 61 volunteer participants. Data were biographic elements, socio-economic profiles, cognitive performance (Corsi test results), psychological battery (anxiety, fatigue, sleep), posture and gait measurement with 4 Imus and a Wii-balance board, and finally the physical activity over a week at home (Armband and Fitbit sensors). These data will help build a control database, to help extract individual profiles with machine learning techniques.

Index Terms - Secondary prevention, stroke, brain traumatic injury, activity incentive, multidimensional data collection

INTRODUCTION

The loss of autonomy, due to age disabilities, chronic pathologies or as a consequence of a sudden illness, is both a personal affliction and a dire socio-economic issue [1]. Autonomy preservation and recovery requires physical activity to tap into physiological resources and neurological plasticity [2]. However, as simple as this goal seems, more than 80% of the patients do not respect simple daily activities recommendations [3]. On the contrary, such patients significantly increase their sedentariness, which notably increases the recurrence risk. Thus, it is urgently needed to find strategies aiming at actively controlling, following, inciting such patients for better practices in a personalized way [4]. A fully ecological follow-up of everyday activities at home could be an optimal solution [5], insofar as any handicap is a complex combination melting previous health issues and contextual problems, such as social and economic factors, as the International Classification of Functioning, Disability, and Health [6] shows. A first step is to ensure adequate data gathering and analysis. Several "commercial off the shelf" sensors exist. However, their reliability and sufficient accessibility for the raw data can be questioned [7].

The aim of the present article is to present an experiment realized during the AMISIA project. AMISIA a multidisciplinary, 36 months Defi CNRS AUTON project, aimed at the secondary prevention of the loss of autonomy for patients with traumatic brain injury and stroke. As "any patient is a unique case," AMISIA proposes an integrated approach, mixing medical health devices, information technology, and human factors to provide patients, health care actors and caregivers from the relatives both the best incentives and high degree of monitoring. Three scientific aims are targeted:

- to study the ability to effectively monitor ones' health by extracting relevant indicators effectively, to factor the information flux and to organize the information flowchart for long-term benefits,

- to set up an adaptive system on which individualized incentive scenarios can be defined and associate to them assistance protocols, using humans or robots,

-to provide a leverage effective feedback based on the information gathered through real rehabilitation in-context sessions, performed on such scenarios.

In accordance with the first aim, we conducted an ad hoc data collection likely to build a forward control database intending to extract individual profiles with machine learning techniques.

II. MATERIAL AND METHOD

I. Participants

Before dealing with patients, we carried out this first work in healthy subjects. Sixty-one participants (age between 18 and 35) volunteered to participate in this study. The inclusion criteria for this study were: "healthy" and "adult". Exclusion criteria for this study were: "subject with visual or perceptual disorders"; "cognitive disorders"; "known neurological or psychiatric disorders"; "participants taking treatment likely to influence memory"; "walking disease" and "subject over 35 years of age". Informed consent was signed before the study began by each participant.

II. Experimental design

The objective of our study was to define criteria allowing us to determine precisely individual strategies to encourage physical activity. For this, each participant carried out a battery of evaluations, which included:

-A recording of physical activity level over seven days (Armband SenseWear Bodymedia). The variables selected for this study are total and active energy expenditure (TEE, AEE), step number (SN) and activity at a low, moderate and vigorous intensity,

- The evaluation of activity level by the International Physical Activity Questionnaire (IPAQ),

-A socio-economic assessment to collect the parents' personal and professional situation, their housing, their daily life, their habits (video games, Internet, social networks, sports activity), their satisfaction and their resources

-An extended assessment of stress, sleep, physical activity engagement, and coping habits in stressful situations using the Coping Inventory for Stressful Situations (CISS), the Epworth Sleepiness Questionnaire, the Profile of Mood States (POMS), the fatigue severity scale (e-Fatigue), the Physical Activity for Health Purposes Motivation Scale (EMAPS), the Treatment-State Anxiety Inventory, the Pittsburgh Sleep Quality Index (PSQI)

-An assessment of the balance. This evaluation was carried out on a Wii-board platform using two methods (open and closed eyes), and information such as the stability index was collected on a tablet[8],

- The walking quality was evaluated based on a 10m round-trip test (walking speed, cycle variability, walking symmetry, double press time). A data recording from 4 inertial units has been done (Xsense®) [9],)

-A mental imagery test consists of performing the above walking test only in mental representation, without moving and with the eyes closed. When the participant starts the imaginary task, he gives the "top" start verbally, and when he thinks he's finished, gives the "top" stop. In parallel, his walking time was timed.

- Finally, each participant carried out a cognitive evaluation based on the Corsi test, in two different modalities [10]: In near space (E-Corsi test: ECT) and far space with space navigation in an environment without spatial landmarks (Virtual Walk-Corsi test: VWCT, see Figure 1) This work is presented in a recently published article [11]

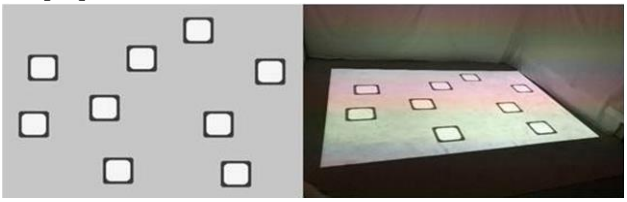

FIGURE 1. SMALL AND LARGE SCALE CORSI TEST.

III. RESULTS

I. Population assessment

Sixty-one participants (20 men and 41 women, 23 ± 3 years), were included in our study. Two groups performed the classical Corsi navigation score: Group A (n = 30), memory span less than 7 and Group B (n = 31), memory span more than 7, the span 7 being the median of our population sample.

II. Cognitive results

For the VWCT, mean memory span for Group A is 5.5±0.7, and 7.6±0.9 ($p<0.001$) for Group B. Both TEE and AEE were significantly higher in Group B (TEE: 2297±269 kcal vs. 2736±585 kcal, p=0.0016; AEE: 667±320 kcal vs. 1017±504 kcal, p=0.0028). Significant correlations are obtained between the score in the VWCT and the TEE ($r=0.51$, $p<0.001$) and the AEE, greater than 3 METs ($r=0.486$, $p<0.001$) (Figure 2). However, we found no difference between groups for the IPAQ score. Additionally, we find, with the socio-demographic questionnaire, that participants from Group B are more prone to play video games that participants from Group A. Fatigue questionnaire results show also that participants from Group A have a higher fatigue level (3.1±1.2) than participants from Group B (2.8±0.9). There is no significant difference between Group A and B for the other variables (Gait quality, posture, anxiety, drowsiness, motivation, sleep). A multiple regression analysis shows that AEE, total physical activity duration and fatigue account for 40% of the memory span variance.

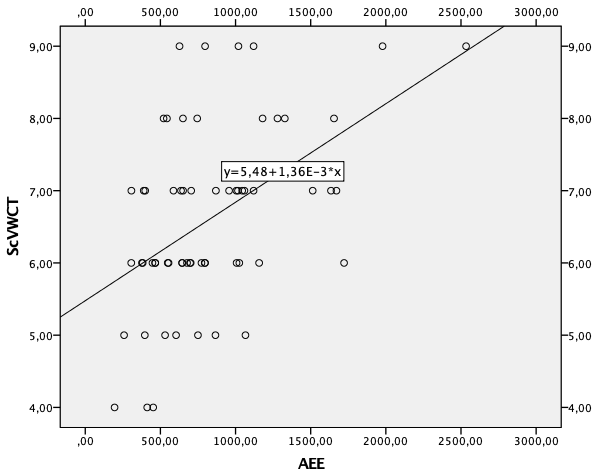

FIGURE 2: RELATIONSHIP BETWEEN ACTIVE ENERGY EXPENDITURE (AEE) AND THE SCORE ON THE WALKING CORSI TEST (SCVWCT)

IV. DISCUSSION

Cognitive disorders are strongly present in traumatic brain injury or stroke patients. It constitutes a limitation for the activity and the return to a healthy social life. This study, even if we included only healthy young subjects, allows us to postulate that the cognitive disorders could be partly explained by the lack of activity of the people, and also by a state of more significant fatigue. Our study reports a few other criteria that can explain the variance of the span. The lack of effect for these criteria can be explained by the characteristics of our subjects, young and healthy. However, better identifying (i) the primary

symptoms of restriction of activity and limitation of participation, and (ii) the criteria explaining the majority of these variations, will undoubtedly help to define the individual strategy of incentive for the activity. If all this analysis can be done via a sensor and an application (adapted dashboard), then it will be easier to follow the patient and advised for a successful home return. And these data will help build a control database, to help extract individual profiles with machine learning techniques. Ultimately, the AMISIA project will focus on three directions.

The first one is the pursuit of the work on data collection, treatment, and interpretation: A set of sensors and traditional approaches will be combined to produce interpretable data for the follow-up and future evaluations [11]. This objective will address the issue of data presentation in personalized scoreboards for the patient, the medical team and the caregivers. Heterogeneous in nature and massive in volume, data will need a flexible storage solution [12]. The ability to insert "on the fly" additional data collection devices or other services will be here addressed.

The second one is the design and the classification of sets of personalized scenarios building blocks: Based on upstream defined indicators and personæ modeling, we shall first develop an adaptive system able to generate personalized scenarios as the concatenation of elementary items aka grains [13]. Thanks to an intuitive interface, the medical team will be able to provide several scenarios, organized in classes. Scenario relevance, ease of use and classes scope will be evaluated.

The third one is the implementation of incentive scenarios: The matter here is to study how to help the participants to recover or discover a beneficial physical activity in a personalized mode. It will combine human and robotic or system assisting mediations to [15, 16]. The acceptability and usability of such interactions and mediation proposals will be evaluated, especially at the social level. The use of artificial intelligence can be an excellent way to monitor and encourage each person's profile. Recent studies such as those by Stein et al. [17] have shown a decrease in weight in obese patients from a robotic system, using artificial intelligence including elements of behavioral therapy.

We have shown in our study that incentive physical activity cannot be based on knowledge of a few parameters such as weight, age, and gender. Other bio-psycho-social parameters must also be included in the model. Further studies, integrating artificial intelligence, will be needed to improve strategies to promote physical activity among patient with loss of autonomy.

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