A Decision-Support Framework for Promoting 
Independent Living and Ageing Well

Antonis S. Billis, Elpiniki Papageorgiou, Christos A. Frantzidis, Marianna S. Tsatali, Anthoula C. Tsalaki, 
and Panagiotis D. Bamidis, Member, IEEE

Abstract—Artificial intelligence and decision support systems of-
fer a plethora of health monitoring capabilities in ambient assisted 
life living environment. Continuous assessment of health indicators for 
elderly people living on their own is of utmost importance, so as 
to prolong their independence and quality of life. Slow varying, 
long-term deteriorating health trends are not easily identifiable in 
seniors. Thus, early sign detection of a specific condition, as well 
as, any likely transition from a healthy state to a pathological one 
are key problems that the herein proposed framework aims at re-
solving. Statistical process control concepts offer a personalized 
approach toward identification of trends that are away from the 
typical behavior or state of the seniors, while fuzzy cognitive maps 
knowledge representation and inference schema have proved to be 
efficient in terms of disease classification. Geriatric depression is 
used as a case study throughout the paper, so to prove the validity 
of the framework, which is planned to be pilot tested with a series 
of lone-living seniors in their own homes.

Index Terms—Data-driven Hebbian learning (DD-NHL), deci-
sion support systems (DSSs), fuzzy cognitive maps (FCMs), 
personalized health, statistical process control.

I. INTRODUCTION

DURING the last few decades, senior population and life ex-
pectancy have been increasing constantly, thereby posing 
the need for preservation of autonomous living for longer pe-
riods of time [1]. Ambient-assisted living (AAL) technologies 
have become a contemporary trend towards the promotion of 
independent living among the elderly and the disabled [2]. Nu-
merous services have been proposed [3] as part of AAL research 
and pilot projects, such as: health monitoring and detection of 
health abnormalities [4], [5], emergency alerting [6], [7], early 
prognosis of chronic conditions [8]–[11], and enablement of 
actions in order to alleviate or prevent disease symptoms [12].

Wearable biosensor systems have been introduced in litera-
ture as multiparametric health-monitoring platforms (for a
review, see [13]). These approaches offer both accurate record-
ing and real-time processing capabilities towards the early 
detection of pathological patterns and medical decision-making.

Despite, the promising results obtained so far, they have not yet 
provided a fully unobtrusive methodology convenient enough 
for seniors [14].

The USEFIL project [15] aims at the promotion of “independent 
living” and “aging well in place” concepts, while respecting 
the privacy feeling of the seniors, applying unobtrusive technol-
ogy to remotely health monitoring. Low-level features extracted 
from the raw sensory data are fused within a data fusion compo-
ent, in order to provide contextualized information in the form 
of high level events [16]. The term “events” is used for either 
measurement-like observations (e.g., a heart rate measurement) 
or fact-like observations (e.g., the person went to sleep). System 
monitoring is organized in three levels: the sensor-specific moni-
toring level, where events are associated with a specific sensor, 
the short-term events monitoring level, providing information 
about the user on a short-term basis (e.g., 1 day), and the long-
term events monitoring level providing long-term information 
as well as trends related to the monitored person, over weeks or months. These three levels of events form a hierarchy, since 
long-term events are detected based on short term events, while 
short-term events are detected based on sensor-level monitor-
ing events. In this respect, sensor-level monitoring events are 
also referred as low-level events, while short-term events are 
referred as high-level events. High-level events along with elec-
tronic health records are regarded as inputs to an intelligent 
processing module, namely the decision support system (DSS), 
which supports several medical decision making tasks, such as 
monitor health assessment indicators on an ongoing basis, diag-
nosis support and risk assessment. The whole information flow 
within the USEFIL system is depicted in Fig. 1.

A. Paper Outline

The paper is structured as follows. First, Section II describes 
how the current work goes beyond the literature’s baseline in 
terms of tele-health monitoring methods. Subsequently, a short 
overview of the framework’s composition and the components’ 
interactions is presented in Section III. Furthermore, in Sec-

Manuscript received January 15, 2014; revised May 5, 2014; accepted June 
27, 2014. Date of publication; date of current version. This work was supported 
in part from the European Union’s Seventh Framework Programme (FP7/2007-
2013) under Grant 288532.

A. S. Billis, C. A. Frantzidis, and P. D. Bamidis are with the Lab 
of Medical Physics, Medical School, Aristotle University of Thessaloniki, 
Thessaloniki 54124, Greece (e-mail: amplis@med.auth.gr; frantz@iti.gr; 
bamidis@med.auth.gr).

E. I. Papageorgiou is with the Department of Informatics and Computer Tech-
nology, Technological Educational Institute of Lamia, Lamia 35100, Greece 
(e-mail: epapageorgiou@teilam.gr).

M. S. Tsatali and A. C. Tsalaki are with the Greek Association of Alzheimer’s 
Disease and Related Disorders, Thessaloniki 54643, Greece (e-mail: mtsatali@ 
yahoo.gr; tsolakiantoula@gmail.com).

Color versions of one or more of the figures in this paper are available online 

Digital Object Identifier 10.1109/JBHI.2014.2336757
depression is employed. This way, we present the multifaceted approach of the framework towards the health monitoring of seniors at any stage.

After Section IV, a description of the datasets used for the evaluation of the proposed framework is provided in Section V. Several artificial scenarios were developed, which simulate: 1) sleep patterns, based on the total amount of sleep seniors get on a daily basis, 2) healthy and depressive-prone elderly profiles, based on risk factors and clinical symptomatology. Finally, Section VII puts the threads together by shedding light on the conducted simulations/experiments and their corresponding results, along with research limitations and further envisaged work.

II. RELATED WORK

Before going any further, we deem it is important to emphasize how much of the components presented in this paper goes beyond the state of the art.

A. Long-Term Analysis—Beyond State-of-the-Art

The majority of already developed decision-support systems mainly focus on the detection of chronic conditions that affect senior citizens [17], [18]. Apart from providing signs of already occurred pathological patterns, the USEFIL DSS approach also includes a trend analysis component. The reason that motivated the design of such a system is to provide not only reactive approaches in case of a life threatening situation (e.g., heart disease), but to detect pathological signs such as deteriorating trends of sleep quality. On the other hand, identification of trends may be useful to reject outliers due to sensor noise and to recognize potential health risks based on deteriorating health trends. So, long-term analysis may be of particular importance in case of slow varying pathological phenomena with preclinical phases of long duration such as cognitive decline and loss of autonomous functioning [19]. Our trend analysis component is inspired by statistical process control techniques for estimating trends, which makes it quite novel. Unlike other approaches that estimate trends in the form of time series [19], [20] the proposed approach constructs confidence intervals defined by lower/upper limits and mean values. Confidence intervals allow the system to detect short-time windows that deviate from these intervals due to acute events or sensor artifacts/outliers. This approach facilitates both the detection of emergency alerts as well as the system’s temporal failure in case of technical problems.

B. Decision Support—Beyond State-of-the-Art

Most of the previous decision support studies have shown that probabilistic networks, cognitive approaches, and fuzzy-logic-based methodologies may be used for medical decision making [21]. Apart from providing decisions regarding mainly diagnosis and treatment suggestions, the probabilistic and cognitive processes seem to be able to cope with inherent uncertainty and a priori knowledge; however, they require enough knowledge acquisition time and huge expert effort. The herein proposed fuzzy cognitive map (FCM)-based methodologies and algorithms for medical decision making and classification, go beyond the state of the art, since: they facilitate doctors’ decision making and act as a proactive and reactive mechanism against health risks.

In the case of classification, unsupervised data-driven nonlinear Hebbian (DD-NHL) algorithm was used for FCM learning using both experts’ knowledge and historical data. In comparison to other machine learning approaches, DD-NHL algorithm exhibits the following advantages: they demand less computational effort, they are less time consuming, and provide promising performance even in cases with small number of instances [22].

III. DSS COMPONENTS

The heterogeneity of the decision tasks for which the USEFIL DSS is responsible, poses the need for a modular architecture. Each component must process a different kind of information and needs to transform its inputs to higher level information so as for it to be exploitable and comprehensible by health practitioners. As shown in Fig. 2, the main DSS components are the following: 1) trend analysis, 2) decision support core, and 3) risk prediction and assessment.
The sensor data fusion component is not part of the DSS, but it serves as an intermediate processing layer between sensor processing components and the DSS. Its main scope is to provide a contextual understanding of the user’s current activities, and actions in the short-term based on low-level events.

The first DSS component is the trend analysis component—inputs the sensor data fusion information, extracts the senior’s baseline profile, and identifies long-term trends. This would result in the annotation of the corresponding symptoms, which subsequently serves as input to the second component (decision support core). Based on the output of the second component and a number of risk factors, the risk prediction and assessment component provides an estimation of health risk. This estimation is quantified into three levels (low/medium/high) and aims at the treatment personalization by recognizing seniors who are at high risk.

Outputs from the first layer (passive health monitoring) characterize the current health status of the senior (physical health, mental, or emotional status), derived from previous DSS components such as the risk prediction and assessment component, whereas the second level of the DSS system (reactive self-treatment) may correlate outputs from the first layer and predefined lifestyle profiles, based on well-defined medical knowledge. This layer is expected to interconnect the various DSS subcomponents and their alerts in order to combine their decisions towards the formation of integrated information regarding the user’s clinical, social, cognitive, and emotional status [23]. However, lifestyle modifications component has not been yet fully implemented and therefore will not be described in the next sections. Still, we add it in DSS schematic diagram for better clarity of the framework’s holistic approach.

IV. METHODOLOGY

A. Long-Term Analysis—Trend Analysis

Identification of trends regarding physiological parameters is based on statistical process control, since each variable under investigation is modeled as a random process with a time-varying mean value and standard deviation. The basic approach is defined by the following steps:

1) Baseline Extraction: The first step towards trend identification is the estimation of a baseline profile through time-series analysis and statistical process control concepts. More specifically, each variable under investigation (e.g., sleeping profile) is modeled as a time-series random process with a time-varying mean value and standard deviation [24]. The computations involved are the following:

2) The baseline profile is consisted of a confidence interval for both the process mean value and the standard deviation. These intervals are defined by the following limits:

\[ \text{lim}_{\text{low}} = \hat{x} - \frac{3\hat{r}}{\sqrt{n}} \]
\[ \text{lim}_{\text{upper}} = \hat{x} + \frac{3\hat{r}}{\sqrt{n}} \]  

(2)

The aforementioned computations result in a personalized baseline profile.

2) Acute Event Detection: Ongoing monitoring of the process under consideration is facilitated through the comparison with the baseline characteristics, and hence, the detection of acute, short-time deviations from the interval defined in the previous step.

3) Long-Term Trend Analysis: Apart from the detection of temporal indicators, long-term monitoring is facilitated by computing the slope of the trend, through the cumulative sum formula. A process is identified, where each run’s mean is subtracted by the mean of the baseline process, and subsequently, it is cumulatively summed with previous calculated differences:

\[ S_i = S_{i-1} + (\bar{x}_i - \hat{x}). \]  

(3)

4) Identification of Sleep Problems: The trend analysis component is demonstrated through the study of daily sleep duration. The proposed methodology involves the formation of a personalized sleep pattern profile during baseline through the adoption of basic concepts derived from statistical process control. Subsequently, short-time deviations from this profile are identified (indicative of significant and acute abnormal sleep events that should be brought into the practitioner’s attention or may indicate noise outliers that should be rejected), while long-term trends are investigated through the cumulative sum approach.

B. Decision Support Core Component for Diagnosis

1) FCMs for Decision Support: FCM is a directed fuzzy signed graph capable of dealing with situations, including uncertain descriptions using similar procedure such as human reasoning does [25], [26]. It consists of nodes/concepts and weighted edges between them. The concepts of the FCM are used to describe the behavior of the system and the signed and weighted interconnections to represent the causal relationships that exist between the concepts. The fuzzy part allows us to have degrees of causality, represented as links between the concepts of these graphs [27].

The construction of an FCM for the modeling of a medical decision making task requires the input of human experience and knowledge of the system under consideration [28], [29]. Once the FCM is constructed, it can receive data from its input concepts, perform reasoning, and infer medical decisions as values of its output concepts. The steps of the FCM model construction and FCM reasoning for medical decision making are described analytically in [28] and [30].

2) FCM Model for Geriatric Depression Diagnosis: The development of a preliminary FCM model for the assessment of
TABLE I

<table>
<thead>
<tr>
<th>Weights of FCM Depression Diagnosis Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1 0</td>
</tr>
<tr>
<td>C2 0</td>
</tr>
<tr>
<td>C3 0.5</td>
</tr>
<tr>
<td>C4 0.25</td>
</tr>
<tr>
<td>C5 0.5</td>
</tr>
<tr>
<td>C6 0.1</td>
</tr>
<tr>
<td>C7 0.1</td>
</tr>
<tr>
<td>C8 0.25</td>
</tr>
<tr>
<td>C9 0.1</td>
</tr>
<tr>
<td>C10 0.65</td>
</tr>
<tr>
<td>C11 0.5</td>
</tr>
<tr>
<td>C12 0.1</td>
</tr>
<tr>
<td>C13 0.1</td>
</tr>
<tr>
<td>C14 0.5</td>
</tr>
</tbody>
</table>

3) FCM Approach for Depression Severity: In the case of determining depression severity, a new dynamic FCM model was developed in order to assess the dynamic nature of the different input fuzzy states of concepts and the different fuzzy relationships between the fuzzy states of concepts.

The development of the dynamic FCM was accomplished through two distinct stages. First, the dynamic FCM was developed as a classic FCM where concepts and causal relationships were identified (check previous section). The concepts can be variables and/or control states. However, the concepts are defined as fuzzy states, taking fuzzy values as inputs. According to these concept states, different fuzzy interrelations exist.

Thus, in order to cope with this fuzzy task and to handle the inherent uncertainty, additional modelling steps were introduced. The dynamic FCM consists, with the exceptions of the concepts and weights, of a weight selection point, and a selection base. The weight selection point gathers all the fuzzy weights and selects only those weights that correspond to the fuzzy input, as determined by trend analysis. The selection base is responsible for the tuning of the fuzzy weights, according to the fuzzy input of each concept, and the production of the final weight matrix used for FCM inference.

The depression severity is based on the same concepts already described for the depression diagnosis task. The decision/output concept of the readjusted FCM is the depression severity. The latter is assigned one of the three states of mild, moderate, or severe, depending on the fuzzy degree of input concepts. The nonlinear relationships that exist between the concepts and especially between the input concepts and severity of depression, can be efficiently coped with the proposed dynamic FCM approach. An example of the proposed dynamic FCM model consisting of five concepts is illustrated in Fig. 4.

As it can be observed from Fig. 4, each one of the four input concepts has a connection with the weight selection point (Ws), which gathers all the fuzzy weights from the related fuzzy inputs/concepts. The weight selection point provides all the fuzzy relationships between the concepts and the selection base. In this case, the Ws include all the fuzzy relationships between experts and following the methodology described in [31]. The final weight matrix is shown in Table I.
the concepts. Next, the selection base, which is responsible for tuning the fuzzy weights according to the fuzzy input of each concept and the depression output, selects only those weights that correspond to the initially determined fuzzy value of the input concept. For example, if the initial fuzzy state of the agitation concept is “medium”, then the selected fuzzy weights are: “low” for emotional status, “low” for reduced interest of daily functioning, and “very high” for Mild state of depression severity. The fuzzy value/state of each input concept is determined by trend analysis. Thus, the selection base produces the final weight matrix used for FCM inference. Therefore, the proposed dynamic FCM is able to efficiently model these interrelationships and make inference of the depression severity degree.

C. DSS Component for Risk Prediction and Assessment

For classification reasons, in order to define for each patient case a category of disease or a level of risk, a classification algorithm based on FCM learning was implemented [32]. The proposed classification algorithm is based on the performance of the DD-NHL, algorithm previously used for autism classification [33]. In our approach, the main steps of the DD-NHL algorithm were used for both learning and testing. We considered 70% of the patient cases to be used for training and 30% for testing, with a random selection of these cases for training and testing at each algorithm performance. During each algorithm run/experiment, the classification accuracy is calculated by the testing cases. The overall classification accuracy is estimated by the mean value of the calculated classification accuracies produced after a large number of experiments.

Summarizing, the proposed classification algorithm consists of the following input and learning and testing phases which are mainly based on the steps of DD-NHL.

Input: For a system with $N$ concepts and $K$ data points, the input data form a matrix $D = [dti]$, where dti corresponds to the value of $i$-th concept ($i = 1, \ldots, N$) at the $t$-th pattern, where $t = 1, \ldots, K$ ($K$ is the number of records), with size $K \times N$, which is called input data matrix. Each row of the given matrix, illustrated as $A(t) = [A1(t), A2(t), \ldots, An(t)]$ where $t = 1, \ldots, K$, stores values of activations of the concepts at the $t$-th iteration.

In the learning phase, the algorithm has to determine the decision boundaries that partition the underlying output vector from step one into three sets, one for each class. For this purpose, one-dimensional decision boundaries were determined by using the minimum Euclidean distance method [34]. Next, in the testing phase, the remaining 30% of the patient cases following the steps of the DD-NHL were classified using the previously produced decision boundaries at each experiment were used to estimate the classification accuracy.

Thus, for a total number of $M$ experiments (in our case, $M = 100$), the mean classifier accuracy was estimated.

1) Risk Assessment of Geriatric Depression: In order to define for each patient case a level of depression, the classification approach for FCM learning is implemented. Before implementation of the classification algorithm, the FCM model concerning the risk of depression must be developed. For the problem of risk of depression, 26 input concepts (representing the factors of risk of depression) and one output concept concerning the category of depression (low, medium, high) were considered.

These 26 input factors defining the concepts of the FCM risk of depression model are as follows:

- C1-Education, C2-Idiosyncratically factors, C3-Recent bereavement C4-Polypharmacy, C5-Chronic stress caused by declining health, family, or marital problems, C6-Major physical and chronic disabling illnesses/Chronic disease, C7-Stopping driving, C8-Excessive alcohol use, C9-Care giving responsibilities for person with a major disease (e.g., dementia), C10-Sexual problems, C11-Adverse drug effects, C12-Hormonal problems, C13-Persistent sleep difficulties, C14-Reduced Mobility—falls, C15-Social disadvantage and low social support, C16-Marital status, C17-Feelings of Worthlessness, C18-Fear of death, C19-Financial problems, C20-Family health problems, C21-Previous depression, C22-Adverse life events (e.g. loss, divorce), C23-Cognitive impairment, C24-Change of self-image/perceived aspect of well being, C25-Retirement, and C26-Religious Beliefs.

Again, following the FCM construction process as described previously (in Section IV-B), an FCM model for risk of depression was constructed. The model consists of 124 weighted interconnections among concepts which were defined by experts’ suggestions. These weighted interconnections constitute the initial weight matrix of the FCM model used in the DD-NHL learning process.

After the FCM learning approach, where the output for each one patient case is calculated, the algorithm must decide on the decision boundaries that partition the underlying output vector into three sets, one for each class. For this purpose, the minimum Euclidean distance method was used [34].

V. DATA PREPARATION AND EXPERIMENTATION

A. Artificial Scenarios

Since no real-life field trials have been accomplished, we decided to validate each DSS component, by developing synthetic

Fig. 4. Dynamic FCM model for depression severity.
TABLE II
SYNOPSIS OF DIFFERENT EXPERIMENTATION DATASETS AND DATA OUTPUTS OF THE DSS COMPONENTS

<table>
<thead>
<tr>
<th>Module</th>
<th>Sub-category</th>
<th>Synthetic Data Size (# senior profile cases)</th>
<th>Ground Truth Output</th>
<th>Output Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trend Analysis</td>
<td>Sleep problems</td>
<td>100</td>
<td>20 Insomnia, 20 Hypersomnia, 20 Normal ($\sigma^2 = 1$), 20 Normal ($\sigma^2 = 4$), 20 Normal ($\sigma^2 = 9$)</td>
<td>[Insomnia, Hypersomnia, Normal)</td>
</tr>
<tr>
<td>Decision Support Core</td>
<td>Depression Diagnosis</td>
<td>516</td>
<td>340 depressive, 176 normal</td>
<td>Binary (Yes/No)</td>
</tr>
<tr>
<td>Risk Prediction and</td>
<td>Depression Severity</td>
<td>63</td>
<td>44 mild/moderate cases, 19 severe</td>
<td>Mild/Moderate, Severe Depression</td>
</tr>
<tr>
<td>Assessment</td>
<td>Risk of future</td>
<td>100</td>
<td>33 low risk, 34 medium risk, 33 high risk</td>
<td>Degree of risk (Low/Medium/High)</td>
</tr>
</tbody>
</table>

![Image]

**Fig. 5.** Indicative baseline sleeping profiles. In the first column, the variation in sleeping hours per short-term window is plotted, while in the second column, process corresponding control limits' amplitude are depicted.

TABLE III
SENSITIVITY AND SPECIFICITY RESULTS OF MODEL VALIDATION

<table>
<thead>
<tr>
<th></th>
<th>Initial values</th>
<th>Neutral values</th>
<th>Transition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>315/340 = 92.65%</td>
<td>280/340 = 82.4%</td>
<td>228/340 = 67.1%</td>
<td></td>
</tr>
<tr>
<td>Specificity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>176/176 = 100%</td>
<td>176/176 = 100%</td>
<td>168/176 = 95.5%</td>
<td></td>
</tr>
</tbody>
</table>

data taking into account up-to-date literature and experts’ opinion. The following subsections present a brief overview of the synthetic data provided for testing and the experimentation that will lead to the results of this research (see Table II).

1) Sleep Profile: The trend analysis framework was validated by monitoring both short- and long-term alterations of the sleeping hours. Our aim was to detect deterioration/improvement patterns. Therefore, the initial test data represented sleeping profiles which correspond to insomnia, hypersonnia, and normal sleeping profiles. Our simulation analysis included 100 instances. The baseline period is divided into a number of overlapping windows ($N = 30$). Each window size was set at $n = 3$ days and the overlapping ratio is 2/3. This resulted to a total duration of 32 days. Twenty five (25) additional time windows of the same size ($n = 3$ days) were available in order to examine acute changes and trends away from baseline.

We tested the algorithm with various synthetic instances as visualized in Fig. 5. The instances were simulated as either normally distributed processes with fixed mean value and standard deviation or demonstrating increase/decrease patterns contaminated with noise modeled as Gaussian processes. Indicative cases are visualized in the following figure (left column) as well as with the mean process interval (right column).

2) Emotional Status: In order to build synthetic scenarios, we consulted two experts, who provided us with the parameters' values (14 concepts as described) and certain rules that apply to geriatric depression symptomatology and diagnosis.

Diagnosis of depression requires existence of at least five symptoms (concepts), including depressive mood and diminished ability of daily living. Extra care was taken regarding the relationship that exists among several symptoms. For example, insomnia/hypersonnia and agitation/retardation concepts are mutually occlusive, since a senior citizen may suffer either from insomnia or hypersonnia and similarly his psychomotor status could be regarded either as agitated or as retarded. On the other hand, he or she may suffer simultaneously from feelings of worthlessness and extreme self-criticism or from diminished ability to think/concentrate and indecisiveness. Therefore, the logical relationship regarding the former set of symptoms is the logical XOR while for the latter sets of concepts the logical OR.

At the experimentation stage, we aimed at building scenarios reflecting as much as possible real data. Therefore, a serious amount of synthetic emotional profiles were developed and annotated by experts (340 depressive and 176 normal cases). Moreover, case homogeneity among marginal and extreme scenarios ensures that the system is able to recognize both “easy” and “difficult” instances of depression symptomatology with the same sensitivity.

3) Severity of Geriatric Depression: Depression severity scenarios were also constructed as part of the tests for the DSS. Specifically, the system tries to perceive the exact inputs and detect depression severity through scenarios identification. The scope of artificial scenarios development is to enable the algorithm to decide whether the patient’s symptoms, by giving their number and frequency levels (expressed in three fuzzy levels of intensity (low/medium/high)), can evaluate depression’s severity (mild/moderate or severe level).
According to experts, inputs which lead to severe depression are those where the majority of symptoms have moderate or severe intensity and frequency, while the analogous scenarios for mild depression included fewer symptoms with mild or moderate intensity and frequency. Sixty three (63) cases were developed and annotated based on the aforementioned assumptions.

4) Risk Prediction of Geriatric Depression: In order to develop artificial scenarios based on real clinical cases, experts combined the risk factors addressed in Section IV-C. Taking into account the differences between risk factors, such as their importance expressed in terms of weighted contribution, their number, and clinical experience, we were able to create one hundred (100) scenarios.

VI. RESULTS

A. Identification of Geriatric Depression Symptomatology

1) Baseline Profile Extraction: The proposed algorithm was used to first estimate the baseline characteristics (mean value and confidence intervals). Aiming to test our system with realistic scenarios, we modeled baseline instances to be nonstationary time-series with underlying dynamics dependent from time variations. The latter was visualized in the last (third) row of Fig. 5, which was consisted of an initial relatively stable period, which was followed by a decline in sleep duration, while the last part is characterized by an increase.

2) Acute Event Detection: Once the participant’s sleep profile has been estimated, the acute event detection procedure is performed by comparing the current window’s temporal characteristics with the baseline profile in terms of the confidence interval. As an example, let us regard the third baseline period (plotted in black). Its baseline mean value is 290.3057 and the confidence interval for the mean value is [279.8104 – 300.8009]. Let us assume now that the current temporal window demonstrates a mean value of 250. This triggers an acute event notification indicative of a sudden sleep duration decrease.

3) Trend Identification: Analysis of long-term trends is performed through the cumulative sum formula as described in Section IV. This analysis enables us to identify slow varying trends even in the presence of noise, outliers, and acute events. Let us consider the following example: a stable condition modeled with mean value 280 h and standard deviation 15 h. In our first case (see Fig. 6; first row), this baseline period was followed by a sudden decrease (acute event) and a stable period with low variability and lower mean value.

The resulted time-series is visualized in the left column (blue color). The underlying trend is visualized in the right column (blue color). The medical expert could observe this sudden decrease and stabilization to a lower mean value by the descending slope. The second row visualizes the same baseline period followed by a gradual increase in sleep duration. This increase is depicted as a long-term increase in the second part of the cumulative sum graph (second row; right Column). Finally, the third row represents a profile with several fluctuations through time. As depicted in the cumulative sum graph (third row; right column), there is an initial decreasing trend followed by an increasing one and resulting to a stable, final state.

B. Identification of Early Depressive Signs

More specifically, we validated our FCM system under three different circumstances. First, we tested the system with an a priori knowledge regarding the patients’ health status—depressed for the depressed cases and healthy for the healthy cases. The results seem to be consistent with the expert’s knowledge and guidelines, and give the model’s accuracy to be 95.15%. Second, we set the initial conditions to correspond to the borderline (C14 = 0.5) and the system’s accuracy was restricted to 88.37% (457/517), since it failed to recognize 60 depressive cases. In a similar way, (transition case), we set the initial healthy conditions to be pathological and the initial pathological conditions to be healthy. Despite the misleading conditions, the system’s accuracy was satisfactory (76.93%).

C. Identification of Geriatric Depression Severity

Sixty three cases were built, following the principles described in the section on depression severity scenarios description. These cases served as the basis for the validation of the developed FCM-based depression severity system. Based on scientific guidelines [35], two neuropsychologists annotated these patient cases into three categories, respectively mild, moderate, and severe depression. Two experiments were conducted in order to determine the accuracy of the FCM methodology. Mild and moderate states were grouped together, since it is too difficult even for the experts to distinguish between the two. In the first experiment, we included cases where either a stable status or a worsening one was hypothesized. Table IV shows the

<table>
<thead>
<tr>
<th># cases</th>
<th>Accuracy</th>
<th>Type of transition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mild/Moderate —— Mild/Moderate</td>
<td>44</td>
<td>100%</td>
</tr>
<tr>
<td>Mild/Moderate —— Severe</td>
<td>19</td>
<td>94.7%</td>
</tr>
<tr>
<td>Total Accuracy</td>
<td>63</td>
<td>98.4%</td>
</tr>
</tbody>
</table>

Fig. 6. Mean values of time windows versus CUMSUM control charts. In the left column, three different trends are depicted with similar baseline characteristics. Corresponding trends are plotted in the right column.
Fig. 7. Decision line for depression severity detection. The FCM algorithm missed just one case out of total 63 simulated cases. Classification of each case was made by comparing the value of the decision concept with the threshold plotted as decision line.

**TABLE V**

<table>
<thead>
<tr>
<th>Type of transition</th>
<th># cases</th>
<th>Accuracy</th>
<th>Type of transition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mild/Moderate → Mild/Moderate</td>
<td>33</td>
<td>100%</td>
<td>Stable</td>
</tr>
<tr>
<td>Severe → Severe</td>
<td>9</td>
<td>88.9%</td>
<td>Stable</td>
</tr>
<tr>
<td>Severe → Mild/Moderate</td>
<td>11</td>
<td>9%</td>
<td>Improvement</td>
</tr>
<tr>
<td>Mild/Moderate → Severe</td>
<td>10</td>
<td>100%</td>
<td>Deterioration</td>
</tr>
<tr>
<td><strong>Total Accuracy</strong></td>
<td>63</td>
<td>82.54%</td>
<td></td>
</tr>
</tbody>
</table>

distribution of these types of cases (Prior Health Status → Current Health Status) and the accuracy of the FCM model. Fig. 7 shows a decision threshold between mild/moderate cases (green cross) and severe ones (red circles).

In the second experiment, we created more challenging transition cases, which also represented improvement of the senior’s emotional status. Table V shows the distribution of these types of cases (Prior Health Status → Current Health Status) and the accuracy of the FCM model. Fig. 8 shows a decision threshold between mild/moderate cases (green cross) and severe ones (red circles).

**D. Risk Prediction of Geriatric Depression**

One hundred (100) scenario-patient cases with low, medium, and high risk of depression were assembled from questionnaires. Using the classification approach of the FCM–DD-NHL learning algorithm, we classified these cases into three categories, considering the learning and testing phases. To estimate the classifier accuracy, 30 cases selected randomly from the initially 100 cases were used for testing, whereas the remaining ones were used for FCM learning. The algorithm performance was evaluated by considering 100 experiments.

At each experiment, 70% of cases were used for learning and 30% for testing randomly selected. The mean value of the classification accuracy was estimated to 78.66%.

Fig. 9 is an indicative experiment run for 30 cases selected randomly from the initial dataset.

Apart from the classification accuracy, precision and recall were calculated for each class (low, medium and high risk) (see Table VI).
VII. DISCUSSION

This piece of research study aimed at presenting a first attempt to develop a modular decision support framework for the promotion of independent living and aging well. Three main components compose the proposed framework: trend analysis, decision support core, and risk prediction and assessment.

The trend analysis component aimed at estimating both the short-term events and long-term conditions in order to provide decisions regarding the chronic conditions affecting the elderly (e.g., cognitive impairment, loss of functional ability, depression, etc.). More specifically, this part of the DSS provides answers to the following questions:

1. How could daily observations be mapped into slow varying trends that may hide gradual health deterioration?
2. Could one detect transition patterns indicative of future deterioration prior to the symptoms’ appearance?
3. Could one estimate chronic alterations in the presence of outliers that may be either due to system failure or due to acute events?

A personalized approach was adopted to face the inherent variability of physiological data. Despite the establishment of generically accepted and well-documented cutoff values for detecting insomnia or hypersomnia, these may vary in each participant. Therefore, it is very important to detect alterations in the light of a personalized sleep model.

Detection of acute events is an extensively studied topic and especially valuable in the case of conditions that endanger the life of senior citizens. However, transient deviations from the developed baseline sleep model may also be due to noise/sensor outliers or due to environmental conditions. These parameters greatly affect the system’s behavior and may supersede real trends, and thus need to be identified and further studied.

The baseline itself may be characterized by underlying dynamics. Moreover, pathology may exist during baseline in case of recruiting participants suffering, e.g., from chronic insomnia. Therefore, the baseline situation is also detected and annotated. The novelty of the proposed approach is that it does not annotate forthcoming changes in terms of group-defined thresholds but is based on individual values. For example, a senior citizen may still suffer from insomnia but its condition may be improved regarding the baseline period. So, our main focus is to detect alterations relative to baseline. Therefore, special attention should be given at the definition of the baseline period. The baseline interval should be defined taking into consideration two facts: 1) avoid influence from transient, fast-varying events (e.g., sensor noise, acute events) and, 1) slow-varying, seasonal effects (e.g., normal decrease in sleep duration due to summer) that may also influence the baseline calculations.

Identifying that a senior has a specific condition, e.g., geriatric depression, is of great significance since this allows certain therapeutic measures to be taken and triggers constant monitoring of the disease evolution. Given the presence of a disease’s symptomatology, the DSS should quantify the extent of the disease and alert the carer by identifying transitions of health state.

The decision support core components have been developed to estimate current health states. Comparison with previous health states is also performed to examine transitions and to monitor the disease progression. Through timely assessment and identification of such transitions, the component is able to generate alerts for the carer. The results, which were evaluated by our experts (neuropsychologists), demonstrate that the system works satisfactory in the sense that a high level of accuracy is achieved.

A modified version of the FCM-based depression diagnosis schema was also introduced, where a dynamic selection process intervenes in order to form the final weight matrix. Experiments were conducted, keeping in mind that the primary goal is to achieve accurate transition state findings. Results from both experiments (stable condition or deteriorating) suggest that the proposed methodology has a satisfactory accuracy in cases where either the emotional status of the person remains stable or is deteriorating.

Finally, an FCM-DDNLH approach has been adopted in order to train the FCM model towards predicting and assessing future health risks, e.g., depression. Mild/moderate cases that were wrongly classified as severe refer to simulated cases where there was an improvement of depression severity. Although, modeling of such transition type among severity states fails to offer even fair reliability, it is of little interest to the doctors, as it represents pretty rare cases and furthermore do not reflect actual patient cases. The rest cases showed pretty accurate results.

The results of all the algorithms used within the proposed framework are promising and suggest that our approach will detect elders either suffering from depressive systems or being at high risk of doing so in the future. Of course, further testing with real-life clinical cases is needed to further confirm this result.

A. Limitations and Future Work

The entire DSS system and its algorithms are based on scenarios developed by experts involved in the USEFIL project. Currently, in this project, there exist no real (senior) sensor data as pilots have not been deployed yet. However, the plan is that over the next few months all system components are integrated together and complete system setups become available for installation in seniors’ homes. This unavailability of real data drove the motivation to initiate the production of synthetic scenarios for DSS training and validation (i.e., pseudo-data).

The main goal of this phase is to simulate real cases towards algorithmic development and testing. Their performance was hypothesized to remain high when processing either simulated or real data by employing an exhaustive search for patterns that are likely (frequently or rarely) to occur during the pilots.
However, it is important to highlight issues that may limit the DSS performance during the pilot phase. These are the variations (artifacts, outliers, sensor malfunction, missing data) that may occur. All these parameters, superimposed on the inherent complexity of human behavior, increase the variability of the data obtained. Aiming to deal with this problem, synthetic patterns were contaminated with noise, which was modeled as a Gaussian statistical process with varying mean values and standard deviations. In addition to the “filtering” taking place during the data fusion process, training the algorithms with a varying degree of noise is expected to enhance the system’s robustness. Finally, there is the case of the temporal lack of sensors due to malfunction or bad use of the equipment. This situation is highly possible to occur and should be considered during the system development. Alternative approaches can be adopted in order to deal with this situation: the DSS can identify, based on previously obtained data, the system’s behavior in terms of its dominant pattern and its dynamics. Then, a data imputation method may take place, similar to the ones reported in [36].

Another issue has to do with the approach followed within the trend analysis component. More specifically, the methodology developed, calculates trends based only to a single parameter. However, most symptoms in the elderly are much more complex and rely to multifactorial information [37]. For example, insomnia/hypersomnia incidents may be characterized in terms of several parameters such as sleep duration, sleep latency, sleep efficiency, increased awakening after sleep onset, multiple long-wake, etc.). In order to extend the proposed analysis, we aim to follow certain steps: the single variable (sleep duration time series) would be extended by a multivariate feature vector which would be consisted of N1 features (sleep duration, latency, number of sleep intervals) and N2 instances.

Then, (1) and (2) described in Section IV-A are performed among vectors and not single variables. Instead of standard deviation, a radius value is defined as parameter and distances among feature vectors are then computed.

VIII. CONCLUSION

In conclusion, it is our belief that the proposed decision support framework has the capacity to accurately evaluate the progression of the seniors’ depressive symptoms and to alert carers, by providing them with useful information for adjusting the patients’ treatment accordingly.

Evaluation of the proposed methodology showed that our approach has a sufficient potential which may be further exploited to identify health risks and to classify seniors into different categories according to their risk levels of becoming diseased. We have already partially applied the proposed framework to other health aspects of the seniors, e.g., activities of daily living monitoring and identification of neurocognitive disease. Still, we expect to gather data from pilots that should start in the near future. Therefore, we will have the opportunity to test the proposed framework under real-life settings and evaluate them in terms of seniors’ quality of life enhancement.

REFERENCES

Christos A. Frantzidis received the Diploma degree in electrical and computer engineering and the M.Sc. degree in medical informatics both from Aristotle University of Thessaloniki (AUTH), Thessaloniki, Greece, in 2006 and 2008, respectively. He is currently working toward the Ph.D. degree in applied neuroscience and works with the Laboratory of Medical Physics, Medical School, AUTH.

His current research interests include affective and neuro-physiological computing, neuro-physiological evaluation of cognitive and physical interventions targeted on elderly populations and medical expert systems.

Marianna S. Tsatali received the Bachelor’s degree from the Department of Psychology, Aristotle University of Thessaloniki (AUTH), Thessaloniki, Greece, in 2004, and the M.Sc. degree from the University of Ioannina, Ioannina, Greece, in 2011. She is currently working toward the Ph.D. degree.

She currently works in Greek Alzheimer Association. Her current research interests include neuropsychology, dementia, nonpharmacological interventions, mood disorders, Parkinson’s disease and emotional function, scales’ validation, and chronic pain.

Ms. Tsatali has been a Member of American Psychological Association (APA Psyc Net) since 2010.

Anthoula C. Tsolaki received the Diploma degree in medicine from the Medical School of Aristotle University of Thessaloniki, Thessaloniki (AUTH), Greece, in 2008. She is currently working toward the Ph.D. degree.

After receiving the Diploma degree, she had worked in the Greek Association of Alzheimer’s Disease and Related Disorders from 2009 to 2013. She is currently working in Information Technologies Institute, Centre for Research and Technology, Hellas, Greece, about risk factor genes for Alzheimer’s Disease and nonpharmacological interventions and collaborates with the Laboratory of Medical Physics, Medical School, AUTH, on gerontechnology projects (USEFIL, DISCOVER, LLM). Her main research interest includes neurodegenerative diseases.

Panagiotis D. Bamidis (M’09) received the Diploma degree in physics from the Aristotle University of Thessaloniki (AUTH), Thessaloniki, Greece, in 1990, the M.Sc. (with distinction) degree in medical physics from the University of Surrey, Guildford, U.K., in 1992, and the Ph.D. degree in bioelectromagnetic brain function analysis and imaging from the Open University, Milton Keynes, U.K., in 1996.

He is currently an Assistant Professor at the Department of Medical Physics, Medical School, AUTH. His research interests include health information management, affective and physiological computing and human–computer interaction, (bio)medical informatics with emphasis on neurophysiological sensing and ambient assisted living, collaborative e-learning, content sharing and repurposing, and medical education informatics.

Antonis S. Billis received the Diploma degree in electrical and computer engineering and the M.Sc. degree in medical informatics, both from Aristotle University of Thessaloniki, Thessaloniki, Greece, in 2007 and 2011, respectively. He also received the Psycho degree in business administration and management from the University of Macedonia, Macedonia, Greece. He is currently working toward the Ph.D. degree in gerontechnology and works with the Laboratory of Medical Physics, Medical School, Aristotle University of Thessaloniki.

His current research interests include medical decision support systems, ambient assisted living technologies, exergaming, and cloud computing.

Mr. Billis has been a Member of the technical chamber of Greece since November 2007.
Q1. Author: Table III is not cited in the text. Please check and cite at an appropriate place in the text.
Q2. Author: Please provide the complete page range in Ref. [8].
Q3. Author: Ref. [38] is not cited in the text. Please check and cite at an appropriate place in the text.
Q4. Author: Please provide the location of the institution where the author “Anthoula C. Tsolaki” is currently working toward the Ph.D. degree.
A Decision-Support Framework for Promoting Independent Living and Ageing Well

Antonis S. Billis, Elpiniki Papageorgiou, Christos A. Frantztidis, Marianna S. Tsatali, Anthoula C. Tsolaki, and Panagiotis D. Bamidis, Member, IEEE

Abstract—Artificial intelligence and decision support systems offer a plethora of health monitoring capabilities in ambient assisted living environment. Continuous assessment of health indicators for elderly people living on their own is of utmost importance, so as to prolong their independence and quality of life. Slow varying, long-term deteriorating health trends are not easily identifiable in seniors. Thus, early sign detection of a specific condition, as well as, any likely transition from a healthy state to a pathological one are key problems that the herein proposed framework aims at resolving. Statistical process control concepts offer a personalized approach toward identification of trends that are away from the atypical behavior or state of the seniors, while fuzzy cognitive maps knowledge representation and inference schema have proved to be efficient in terms of disease classification. Geriatric depression is used as a case study throughout the paper, so to prove the validity of the framework, which is planned to be pilot tested with a series of lone-living seniors in their own homes.

Index Terms—Data-driven Hebbian learning (DD-NHL), decision support systems (DSSs), fuzzy cognitive maps (FCMs), personalized health, statistical process control.

I. INTRODUCTION

During the last few decades, senior population and life expectancy have been increasing constantly, thereby posing the need for preservation of autonomous living for longer periods of time [1]. Ambient-assisted living (AAL) technologies have become a contemporary trend towards the promotion of independent living among the elderly and the disabled [2]. Numerous services have been proposed [3] as part of AAL research and pilot projects, such as: health monitoring and detection of health abnormalities [4], [5], emergency alerting [6], [7], early prognosis of chronic conditions [8]–[11], and enablement of actions in order to alleviate or prevent disease symptoms [12]. Wearable biosensor systems have been introduced in literature as multiparametric health-monitoring platforms (for a review, see [13]). These approaches offer both accurate recording and real-time processing capabilities towards the early detection of pathological patterns and medical decision-making. Despite the promising results obtained so far, they have not yet provided a fully unobtrusive methodology convenient enough for seniors [14].

The USEFIL project [15] aims at the promotion of “independent living” and “aging well in place” concepts, while respecting the privacy feeling of the seniors, applying unobtrusive technology to remotely health monitoring. Low-level features extracted from the raw sensory data are fused within a data fusion component, in order to provide contextualized information in the form of high level events [16]. The term “events” is used for either measurement-like observations (e.g., a heart rate measurement) or fact-like observations (e.g., the person went to sleep). System monitoring is organized in three levels: the sensor-specific monitoring level, where events are associated with a specific sensor, the short-term events monitoring level, providing information about the user on a short-term basis (e.g., 1 day), and the long-term events monitoring level providing long-term information as well as trends related to the monitored person, over weeks or months. These three levels of events form a hierarchy, since long-term events are detected based on short term events, while short-term events are detected based on sensor-level monitoring events. In this respect, sensor-level monitoring events are also referred as low-level events, while short-term events are referred as high-level events. High-level events along with electronic health records are regarded as inputs to an intelligent processing module, namely the decision support system (DSS), which supports several medical decision making tasks, such as monitor health assessment indicators on an ongoing basis, diagnosis support and risk assessment. The whole information flow within the USEFIL system is depicted in Fig. 1.

A. Paper Outline

The paper is structured as follows. First, Section II describes how the current work goes beyond the literature’s baseline in terms of tele-health monitoring methods. Subsequently, a short overview of the framework’s composition and the components’ interactions is presented in Section III. Furthermore, in Section IV, we provide the main algorithms employed for the trend analysis, the decision support for diagnosis, and the health risk prediction problems. Those methodologies are demonstrated through the geriatric depression scenario. More specifically, depressive symptoms, such as sleep problems (insomnia) are explored, identification of depression early existence is facilitated, and disease progression is examined. Finally, risk prediction for

Manuscript received January 15, 2014; revised May 5, 2014; accepted June 27, 2014. Date of publication; date of current version. This work was supported in part from the European Union’s Seventh Framework Programme (FP7/2007-2013) under Grant 288532.

A. S. Billis, C. A. Frantztidis, and P. D. Bamidis are with the Lab of Medical Physics, Medical School, Aristotle University of Thessaloniki, Thessaloniki 54124, Greece (e-mail: amphilis@med.auth.gr; frantz@iti.gr; bamidis@med.auth.gr).

E. I. Papageorgiou is with the Department of Informatics and Computer Technology, Technological Educational Institute of Lamia, Lamia 35100, Greece (e-mail: epapageorgiou@teilam.gr).

M. S. Tsatali and A. C. Tsoaki are with the Greek Association of Alzheimer’s Disease and Related Disorders, Thessaloniki 54643, Greece (e-mail: mtsatali@yahoo.gr; tsolakiantroula@gmail.com).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/JBHI.2014.2336757
depression is employed. This way, we present the multifaceted approach of the framework towards the health monitoring of seniors at any stage.

After Section IV, a description of the datasets used for the evaluation of the proposed framework is provided in Section V. Several artificial scenarios were developed, which simulate: 1) sleep patterns, based on the total amount of sleep seniors get on a daily basis, 2) healthy and depressive-prone elderly profiles, based on risk factors and clinical symptomatology.

Finally, Section VII puts the threads together by shedding light on the conducted simulations/experiments and their corresponding results, along with research limitations and further envisaged work.

II. RELATED WORK

Before going any further, we deem it is important to emphasize how each of the components presented in this paper goes beyond the state of the art.

A. Long-Term Analysis—Beyond State-of-the-Art

The majority of already developed decision-support systems mainly focus on the detection of chronic conditions that affect senior citizens [17], [18]. Apart from providing signs of already occurred pathological patterns, the USEFIL DSS approach also includes a trend analysis component. The reason that motivated the design of such a system is to provide not only reactive approaches in case of a life threatening situation (e.g., heart disease), but to detect pathological signs such as deteriorating trends of sleep quality. On the other hand, identification of trends may be useful to reject outliers due to sensor noise and to recognize potential health risks based on deteriorating health trends. So, long-term analysis may be of particular importance in case of slow varying pathological phenomena with preclinical phases of long duration such as cognitive decline and loss of autonomous functioning [19]. Our trend analysis component is inspired by statistical process control techniques for estimating trends, which makes it quite novel. Unlike other approaches that estimate trends in the form of time series [19], [20] the proposed approach constructs confidence intervals defined by lower/upper limits and mean values. Confidence intervals allow the system to detect short-time windows that deviate from these intervals due to acute events or sensor artifacts/outliers. This approach facilitates both the detection of emergency alerts as well as the system’s temporal failure in case of technical problems.

B. Decision Support—Beyond State-of-the-Art

Most of the previous decision support studies have shown that probabilistic networks, cognitive approaches, and fuzzy-logic-based methodologies may be used for medical decision making [21]. Apart from providing decisions regarding mainly diagnosis and treatment suggestions, the probabilistic and cognitive processes seem to be able to cope with inherent uncertainty and a priori knowledge; however, they require enough knowledge acquisition time and huge expert effort. The herein proposed fuzzy cognitive map (FCM)-based methodologies and algorithms for medical decision making and classification, go beyond the state of the art, since: they facilitate doctors’ decision making and act as a proactive and reactive mechanism against health risks.

In the case of classification, unsupervised data-driven nonlinear Hebbian (DD-NHL) algorithm was used for FCM learning using both experts’ knowledge and historical data. In comparison to other machine learning approaches, DD-NHL algorithm exhibits the following advantages: they demand less computational effort, they are less time consuming, and provide promising performance even in cases with small number of instances [22].

III. DSS COMPONENTS

The heterogeneity of the decision tasks for which the USEFIL DSS is responsible, poses the need for a modular architecture. Each component must process a different kind of information and needs to transform its inputs to higher level information so as for it to be exploitable and comprehensible by health practitioners. As shown in Fig. 2, the main DSS components are the following: 1) trend analysis, 2) decision support core, and 3) risk prediction and assessment.
The sensor data fusion component is not part of the DSS, but it serves as an intermediate processing layer between sensor processing components and the DSS. Its main scope is to provide a contextual understanding of the user’s current activities, and actions in the short-term based on low-level events.

The first DSS component is the trend analysis component—inputs the sensor data fusion information, extracts the senior’s baseline profile, and identifies long-term trends. This would result in the annotation of the corresponding symptoms, which subsequently serves as input to the second component (decision support core). Based on the output of the second component and a number of risk factors, the risk prediction and assessment component provides an estimation of health risk. This estimation is quantified into three levels (low/medium/high) and aims at the treatment personalization by recognizing seniors who are at high risk.

Outputs from the first layer (passive health monitoring) characterize the current health status of the senior (physical health, mental, or emotional status), derived from previous DSS components such as the risk prediction and assessment component, whereas the second level of the DSS system (reactive self-treatment) may correlate outputs from the first layer and predefined lifestyle profiles, based on well-defined medical knowledge. This layer is expected to interconnect the various DSS subcomponents and their alerts in order to combine their decisions towards the formation of integrated information regarding the user’s clinical, social, cognitive, and emotional status [23].

However, lifestyle modifications component has not been yet fully implemented and therefore will not be described in the next sections. Still, we add it in DSS schematic diagram for better clarity of the framework’s holistic approach.

IV. METHODOLOGY

A. Long-Term Analysis—Trend Analysis

Identification of trends regarding physiological parameters is based on statistical process control, since each variable under investigation is modeled as a random process with a time-varying mean value and standard deviation. The basic approach is defined by the following steps:

1) Baseline Extraction: The first step towards trend identification is the estimation of a baseline profile through time-series analysis and statistical process control concepts. More specifically, each variable under investigation (e.g., sleeping profile) is modeled as a time-series random process with a time-varying mean value and standard deviation [24]. The computations involved are the following:

1) Time-series observations are divided into \( n \) overlapping windows. The mean \( \bar{x} \) and the standard deviation \( \bar{r} \) of each time window are computed. Then, the mean value and the standard deviation of the entire process are computed as follows:

\[
\hat{x} = \text{mean}\{\bar{x}\} \\
\hat{r} = \text{mean}\{\bar{r}\}.  
\] (1)

2) The baseline profile is consisted of a confidence interval for both the process mean value and the standard deviation. These intervals are defined by the following limits:

\[
\lim_{\text{low}} = \hat{x} - \frac{3\hat{r}}{\sqrt{n}} \\
\lim_{\text{upper}} = \hat{x} + \frac{3\hat{r}}{\sqrt{n}}  
\] (2)

The aforementioned computations result in a personalized baseline profile.

2) Acute Event Detection: Ongoing monitoring of the process under consideration is facilitated through the comparison with the baseline characteristics, and hence, the detection of acute, short-time deviations from the interval defined in the previous step.

3) Long-Term Trend Analysis: Apart from the detection of temporal indicators, long-term monitoring is facilitated by computing the slope of the trend, through the cumulative sum formula. A process is identified, where each run’s mean is subtracted by the mean of the baseline process, and subsequently, it is cumulatively summed with previous calculated differences:

\[
S_t = S_{t-1} + (\bar{x}_t - \hat{x}).  
\] (3)

4) Identification of Sleep Problems: The trend analysis component is demonstrated through the study of daily sleep duration. The proposed methodology involves the formation of a personalized sleep pattern profile during baseline through the adoption of basic concepts derived from statistical process control. Subsequently, short-term deviations from this profile are identified (indicative of significant and acute abnormal sleep events that should be brought into the practitioner’s attention or may indicate noise outliers that should be rejected), while long-term trends are investigated through the cumulative sum approach.

B. Decision Support Core Component for Diagnosis

1) FCMs for Decision Support: FCM is a directed fuzzy signed graph capable of dealing with situations, including uncertain descriptions using similar procedure such as human reasoning. It consists of nodes/concepts and weighted edges between them. The concepts of the FCM are used to describe the behavior of the system and the signed and weighted interconnections to represent the causal relationships that exist between the concepts. The fuzzy part allows us to have degrees of causality, represented as links between the concepts of these graphs [27].

The construction of an FCM for the modeling of a medical decision making task requires the input of human experience and knowledge of the system under consideration. Once the FCM is constructed, it can receive data from its input concepts, perform reasoning, and infer medical decisions as values of its output concepts. The steps of the FCM model construction and FCM reasoning for medical decision making are described analytically in [28] and [30].

2) FCM Model for Geriatric Depression Diagnosis: The development of a preliminary FCM model for the assessment of
geriatric depression was presented at [31]. A revised model has been developed—concepts were limited only to the set relevant to clinical guidelines (DSM IV)—thus resulting into the following knowledge representation scheme, depicted in Fig. 3. This model consists of 14 concepts: C1: Psychomotor Agitation, C2: Psychomotor Retardation, C3: Depressive Mood, C4: Reduced Interest for Daily Functioning, C5: Insomnia, C6: Hypersomnia, C7: Fatigue or Loss of Energy, C8: Recurrent Thoughts of Death, C9: Loss of Appetite, C10: Diminished Ability to Think or Concentrate, C11: Indecisiveness, C12: Feelings of Worthlessness, C13: Extreme Self-Criticism, and C14: Depression (Decision concept).

Each concept is represented by a binary state, defining either the presence or the absence of the concept. The weights of the proposed model are calculated based on input provided by experts and following the methodology described in [31]. The final weight matrix is shown in Table I.

3) FCM Approach for Depression Severity: In the case of determining depression severity, a new dynamic FCM model was developed in order to assess the dynamic nature of the different input fuzzy states of concepts and the different fuzzy relationships between the fuzzy states of concepts.

The development of the dynamic FCM was accomplished through two distinct stages. First, the dynamic FCM was developed as a classic FCM where concepts and causal relationships were identified (check previous section). The concepts can be variables and/or control states. However, the concepts are defined as fuzzy states, taking fuzzy values as inputs. According to these concept states, different fuzzy interrelations exist.

Thus, in order to cope with this fuzzy task and to handle the inherent uncertainty, additional modeling steps were introduced. The dynamic FCM consists, with the exceptions of the concepts and weights, of a weight selection point, and a selection base. The weight selection point gathers all the fuzzy weights and selects only those weights that correspond to the fuzzy input, as determined by trend analysis. The selection base is responsible for the tuning of the fuzzy weights, according to the fuzzy input of each concept, and the production of the final weight matrix used for FCM inference.

The depression severity is based on the same concepts already described for the depression diagnosis task. The decision/output concept of the readjusted FCM is the depression severity. The latter is assigned one of the three states of mild, moderate, or severe, depending on the fuzzy degree of input concepts. The nonlinear relationships that exist between the concepts and especially between the input concepts and severity of depression, can be efficiently coped with the proposed dynamic FCM approach. An example of the proposed dynamic FCM model consisting of five concepts is illustrated in Fig. 4.

As it can be observed from Fig. 4, each one of the four input concepts has a connection with the weight selection point (Ws), which gathers all the fuzzy weights from the related fuzzy inputs/concepts. The weight selection point provides all the fuzzy relationships between the concepts and the selection base. In this case, the Ws include all the fuzzy relationships between

### TABLE I
WEIGHTS OF FCM DEPRESSION DIAGNOSIS MODEL

<table>
<thead>
<tr>
<th></th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>C6</th>
<th>C7</th>
<th>C8</th>
<th>C9</th>
<th>C10</th>
<th>C11</th>
<th>C12</th>
<th>C13</th>
<th>C14</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>0</td>
<td>0</td>
<td>0.25</td>
<td>0.25</td>
<td>0.5</td>
<td>0.1</td>
<td>0.5</td>
<td>0.1</td>
<td>0.25</td>
<td>0.65</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>C2</td>
<td>0</td>
<td>0.65</td>
<td>0.65</td>
<td>0.5</td>
<td>0.65</td>
<td>0.65</td>
<td>0.25</td>
<td>0.5</td>
<td>0.65</td>
<td>0.65</td>
<td>0.65</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>C3</td>
<td>0.5</td>
<td>0.8</td>
<td>0</td>
<td>0.8</td>
<td>0.65</td>
<td>0.5</td>
<td>0.65</td>
<td>0.25</td>
<td>0.8</td>
<td>0.25</td>
<td>0.8</td>
<td>0.25</td>
<td>0.1</td>
<td>0.65</td>
</tr>
<tr>
<td>C4</td>
<td>0.25</td>
<td>0.65</td>
<td>0.8</td>
<td>0</td>
<td>0.25</td>
<td>0.65</td>
<td>0.25</td>
<td>0.25</td>
<td>0.5</td>
<td>0.8</td>
<td>0.65</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>C5</td>
<td>0.5</td>
<td>0.65</td>
<td>0.8</td>
<td>0.65</td>
<td>0</td>
<td>0.5</td>
<td>0.8</td>
<td>0.25</td>
<td>0.25</td>
<td>0.8</td>
<td>0.25</td>
<td>0.1</td>
<td>0.1</td>
<td>0.65</td>
</tr>
<tr>
<td>C6</td>
<td>0.1</td>
<td>0.65</td>
<td>0.5</td>
<td>0.65</td>
<td>0</td>
<td>0</td>
<td>0.25</td>
<td>0.25</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.25</td>
<td>0.25</td>
<td>0.65</td>
</tr>
<tr>
<td>C7</td>
<td>0.1</td>
<td>0.8</td>
<td>0.65</td>
<td>0.65</td>
<td>0.25</td>
<td>0.65</td>
<td>0</td>
<td>0.5</td>
<td>0.5</td>
<td>0.65</td>
<td>0.65</td>
<td>0.8</td>
<td>0.5</td>
<td>0.65</td>
</tr>
<tr>
<td>C8</td>
<td>0.25</td>
<td>0.5</td>
<td>0.8</td>
<td>1</td>
<td>0.65</td>
<td>0.25</td>
<td>0.25</td>
<td>0</td>
<td>0</td>
<td>0.65</td>
<td>0.65</td>
<td>0.8</td>
<td>0.65</td>
<td>0.65</td>
</tr>
<tr>
<td>C9</td>
<td>0.1</td>
<td>0.65</td>
<td>0.25</td>
<td>0.5</td>
<td>0.25</td>
<td>0.25</td>
<td>0.5</td>
<td>0.8</td>
<td>0.1</td>
<td>0</td>
<td>0.5</td>
<td>0.1</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>C10</td>
<td>0.65</td>
<td>0.25</td>
<td>0.5</td>
<td>0.25</td>
<td>0.25</td>
<td>0.25</td>
<td>0.5</td>
<td>0.65</td>
<td>0.1</td>
<td>0.1</td>
<td>0</td>
<td>0.5</td>
<td>0.65</td>
<td>0.65</td>
</tr>
<tr>
<td>C11</td>
<td>0.5</td>
<td>0.1</td>
<td>0.25</td>
<td>0.5</td>
<td>0.5</td>
<td>0.25</td>
<td>0.65</td>
<td>0.1</td>
<td>0.1</td>
<td>0</td>
<td>0.5</td>
<td>0.65</td>
<td>0.65</td>
<td>0.5</td>
</tr>
<tr>
<td>C12</td>
<td>0.1</td>
<td>0.65</td>
<td>1</td>
<td>0.8</td>
<td>0.65</td>
<td>0.5</td>
<td>0.5</td>
<td>0.8</td>
<td>0</td>
<td>0.5</td>
<td>0.65</td>
<td>0.8</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>C13</td>
<td>0.1</td>
<td>0.65</td>
<td>0.8</td>
<td>0.65</td>
<td>0.65</td>
<td>0.25</td>
<td>0.65</td>
<td>0.65</td>
<td>0.5</td>
<td>0.65</td>
<td>0.65</td>
<td>0.8</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C14</td>
<td>0.5</td>
<td>0.8</td>
<td>1</td>
<td>0.8</td>
<td>0.65</td>
<td>0.65</td>
<td>0.65</td>
<td>0.65</td>
<td>0.8</td>
<td>0.65</td>
<td>0.65</td>
<td>0</td>
<td>0.65</td>
<td>0.65</td>
</tr>
</tbody>
</table>

Fig. 3. FCM model for depression diagnosis.
where 

\[ N \]

is the number of records, with size 

\[ K \times N \]

which is called input data matrix. Each row of the given matrix, illustrated as 

\[ A(t) = [A_1(t), A_2(t), \ldots, A_n(t)] \]

where 

\[ t = 1, \ldots, K \]

stores values of activations of the concepts at the 

\[ t \]-th iteration.

In the learning phase, the algorithm has to determine the decision boundaries that partition the underlying output vector from step one into three sets, one for each class. For this purpose, one-dimensional decision boundaries were determined by using the minimum Euclidean distance method [34]. Next, in the testing phase, the remaining 30% of the patient cases following the steps of the DD-NHL were classified using the previously produced decision boundaries at each experiment were used to estimate the classification accuracy.

Thus, for a total number of M experiments (in our case, 

\[ M = 100 \]

), the mean classifier accuracy was estimated.

1) Risk Assessment of Geriatric Depression: In order to define for each patient case a level of depression, the classification approach for FCM learning is implemented. Before implementation of the classification algorithm, the FCM model concerning the risk of depression must be developed. For the problem of risk of depression, 26 input concepts (representing the factors of risk of depression) and one output concept concerning the category of depression (low, medium, high) were considered.

These 26 input factors defining the concepts of the FCM risk of depression model are as follows:

- C1-Education, C2-Idiosyncratically factors, C3-Recent bereavement C4-Polypharmacy, C5-Chronic stress caused by declining health, family, or marital problems, C6-Major physical and chronic disabling illnesses/Chronic disease, C7-Stopping driving, C8-Excessive alcohol use, C9-Care giving responsibilities for persons with a major disease (e.g., dementia), C10-Sexual problems, C11-Adverse drug effects, C12-Hormonal problems, C13-Persistent sleep difficulties, C14-Reduced Mobility –Falls, C15-Social disadvantage and low social support, C16-Marital status, C17-Feelings of Worthlessness, C18-Fear of death, C19-Financial problems, C20-Family health problems, C21-Previous depression, C22-Adverse life events (e.g. loss, divorce), C23-Cognitive impairment, C24-Change of self-image/perceived aspect of well being, C25-Retirement, and C26-Religious Beliefs.

Again, following the FCM construction process as described previously (in Section IV-B), an FCM model for risk of depression was constructed. The model consists of 124 weighted interconnections among concepts which were defined by experts’ suggestions. These weighted interconnections constitute the initial weight matrix of the FCM model used in the DD-NHL learning process.

After the FCM learning approach, where the output for each one patient case is calculated, the algorithm must decide on the decision boundaries that partition the underlying output vector into three sets, one for each class. For this purpose, the minimum Euclidean distance method was used [34].

V. DATA PREPARATION AND EXPERIMENTATION

A. Artificial Scenarios

Since no real-life field trials have been accomplished, we decided to validate each DSS component, by developing synthetic
We tested the algorithm with various synthetic instances as visualized in Fig. 5. The instances were simulated as either normally distributed processes with fixed mean value and standard deviation or demonstrating increase/decrease patterns contaminated with noise modeled as Gaussian processes. Indicative baseline sleeping profiles. In the first column, the variation in sleeping hours per short-term window is plotted, while in the second column, process corresponding control limits’ amplitude are depicted.

At the experimentation stage, we aimed at building scenarios reflecting as much as possible real data. Therefore, a serious amount of synthetic emotional profiles were developed and annotated by experts (340 depressive and 176 normal cases). Moreover, case homogeneity among marginal and extreme scenarios ensures that the system is able to recognize both “easy” and “difficult” instances of depression symptomatology with the same sensitivity.

3) Severity of Geriatric Depression: Depression severity scenarios were also constructed as part of the tests for the DSS. Specifically, the system tries to perceive the exact inputs and detect depression severity through scenarios identification. The scope of artificial scenarios development is to enable the algorithm to decide whether the patient’s symptoms, by giving their number and frequency levels (expressed in three fuzzy levels of intensity (low/medium/high)), can evaluate depression’s severity (mild/moderate or severe level).
According to experts, inputs which lead to severe depression are those where the majority of symptoms have moderate or severe intensity and frequency, while the analogous scenarios for mild depression included fewer symptoms with mild or moderate intensity and frequency. Sixty-three (63) cases were developed and annotated based on the aforementioned assumptions.

4) Risk Prediction of Geriatric Depression: In order to develop artificial scenarios based on real clinical cases, experts combined the risk factors addressed in Section IV-C. Taking into account the differences between risk factors, such as their importance expressed in terms of weighted contribution, their number, and clinical experience, we were able to create one hundred (100) scenarios.

VI. RESULTS
A. Identification of Geriatric Depression Symptomatology

1) Baseline Profile Extraction: The proposed algorithm was used to estimate the baseline characteristics (mean value and confidence intervals). Aiming to test our system with realistic scenarios, we modeled baseline instances to be nonstationary time-series with underlying dynamics dependent from time variations. The latter was visualized in the last (third) row of Fig. 5, which was consisted of an initial relatively stable period, which was followed by a decline in sleep duration, while the last part is characterized by an increase.

2) Acute Event Detection: Once the participant’s sleep profile has been estimated, the acute event detection procedure is performed by comparing the current window’s temporal characteristics with the baseline profile in terms of the confidence interval. As an example, let us regard the third baseline period (plotted in black). Its baseline mean value is 290.3057 and the confidence interval for the mean value is [279.8104–300.8009]. Let us assume now that the current temporal window demonstrates a mean value of 250. This triggers an acute event notification indicative of a sudden sleep duration decrease.

3) Trend Identification: Analysis of long-term trends is performed through the cumulative sum formula as described in Section IV. This analysis enables us to identify slow varying trends even in the presence of noise, outliers, and acute events. Let us consider the following example: a stable condition modeled with mean value 280 h and standard deviation 15 h. In our first case (see Fig. 6; first row), this baseline period was followed by a sudden decrease (acute event) and a stable period with low variability and lower mean value.

The resulted time-series is visualized in the left column (blue color). The underlying trend is visualized in the right column (blue color). The medical expert could observe this sudden decrease and stabilization to a lower mean value by the descending slope. The second row visualizes the same baseline period followed by a gradual increase in sleep duration. This increase is depicted as a long-term increase in the second part of the cumulative sum graph (second row; right Column). Finally, the third row represents a profile with several fluctuations through time. As depicted in the cumulative sum graph (third row; right column), there is an initial decreasing trend followed by an increasing one and resulting to a stable, final state.

B. Identification of Early Depressive Signs

More specifically, we validated our FCM system under three different circumstances. First, we tested the system with a prior knowledge regarding the patients’ health status — depressed for the depressed cases and healthy for the healthy cases. The results seem to be consistent with the expert’s knowledge and guidelines, and give the model’s accuracy to be 95.15%. Second, we set the initial conditions to correspond to the borderline (C14 = 0.5) and the system’s accuracy was restricted to 88.37% (457/517), since it failed to recognize 60 depressive cases. In a similar way, (transition case), we set the initial healthy conditions to be pathological and the initial pathological conditions to be healthy. Despite the misleading conditions, the system’s accuracy was satisfactory (76.93%).

C. Identification of Geriatric Depression Severity

Sixty-three cases were built, following the principles described in the section on depression severity scenarios description. These cases served as the basis for the validation of the developed FCM-based depression severity system. Based on scientific guidelines [35], two neuropsychologists annotated these patient cases into three categories, respectively mild, moderate, and severe depression. Two experiments were conducted in order to determine the accuracy of the FCM methodology. Mild and moderate states were grouped together, since it is too difficult even for the experts to distinguish between the two. In the first experiment, we included cases where either a stable status or a worsening one was hypothesized. Table IV shows the

---

TABLE IV

<table>
<thead>
<tr>
<th># cases</th>
<th>Accuracy</th>
<th>Type of transition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mild/Moderate — Mild/Moderate</td>
<td>44</td>
<td>100%</td>
</tr>
<tr>
<td>Mild/Moderate — Severe</td>
<td>19</td>
<td>94.7%</td>
</tr>
<tr>
<td>Total Accuracy</td>
<td>63</td>
<td>98.4%</td>
</tr>
</tbody>
</table>

---
Fig. 7: Decision line for depression severity detection. The FCM algorithm missed just one case out of total 63 simulated cases. Classification of each case was made by comparing the value of the decision concept with the threshold plotted as decision line.

### TABLE V

**Example cases showing the estimated severity**

<table>
<thead>
<tr>
<th># cases</th>
<th>Accuracy</th>
<th>Type of transition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mild/Moderate → Mild/Moderate</td>
<td>33</td>
<td>100%</td>
</tr>
<tr>
<td>Severe → Severe</td>
<td>9</td>
<td>88.9%</td>
</tr>
<tr>
<td>Severe → Mild/Moderate</td>
<td>11</td>
<td>9%</td>
</tr>
<tr>
<td>Mild/Moderate → Severe</td>
<td>10</td>
<td>100%</td>
</tr>
<tr>
<td>Total Accuracy</td>
<td>63</td>
<td>82.54%</td>
</tr>
</tbody>
</table>

distribution of these types of cases (Prior Health Status → Current Health Status) and the accuracy of the FCM model. Fig. 7 shows a decision threshold between mild/moderate cases (green cross) and severe ones (red circles).

In the second experiment, we created more challenging transition cases, which also represented improvement of the senior’s emotional status. Table V shows the distribution of these types of cases (Prior Health Status → Current Health Status) and the accuracy of the FCM model. Fig. 8 shows a decision threshold between mild/moderate cases (green cross) and severe ones (red circles).

D. Risk Prediction of Geriatric Depression

One hundred (100) scenario-patient cases with low, medium, and high risk of depression were assembled from questionnaires. Using the classification approach of the FCM–DD-NHL learning algorithm, we classified these cases into three categories, considering the learning and testing phases. To estimate the classifier accuracy, 30 cases selected randomly from the initially 100 cases were used for testing, whereas the remaining ones were used for FCM learning. The algorithm performance was evaluated by considering 100 experiments.

At each experiment, 70% of cases were used for learning and 30% for testing randomly selected. The mean value of the classification accuracy was estimated to 78.66%.

Fig. 9 is an indicative experiment run for 30 cases selected randomly from the initial dataset.

Apart from the classification accuracy, precision and recall were calculated for each class (low, medium and high risk) (see Table VI).


VII. DISCUSSION

This piece of research study aimed at presenting a first attempt to develop a modular decision support framework for the promotion of independent living and aging well. Three main components compose the proposed framework: trend analysis, decision support core, and risk prediction and assessment.

The trend analysis component aimed at estimating both the short-term events and long-term conditions in order to provide decisions regarding the chronic conditions affecting the elderly (e.g., cognitive impairment, loss of functional ability, depression, etc.). Moreover, this part of the DSS provides answers to the following questions:

1) How could daily observations be mapped into slow varying trends that may hide gradual health deterioration?
2) Could one detect transition patterns indicative of future deterioration prior to the symptoms’ appearance?
3) Could one estimate chronic alterations in the presence of outliers that may be either due to system failure or due to acute events?

A personalized approach was adopted to face the inherent variability of physiological data. Despite the establishment of generically accepted and well-documented cutoff values for detecting insomnia or hypersomnia, these may vary in each participant. Therefore, it is very important to detect alterations in the light of a personalized sleep model.

Detection of acute events is an extensively studied topic and especially valuable in the case of conditions that endanger the life of senior citizens. However, transient deviations from the developed baseline sleep model may also be due to noise/sensor outliers or due to environmental conditions. These parameters greatly affect the system’s behavior and may supersede real trends, and thus need to be identified and further studied.

The baseline itself may be characterized by underlying dynamics. Moreover, pathology may exist during baseline in case of recruiting participants suffering, e.g., from chronic insomnia. Therefore, the baseline situation is also detected and annotated. The novelty of the proposed approach is that it does not annotate forthcoming changes in terms of group-defined thresholds but is based on individual values. For example, a senior citizen may still suffer from insomnia but its condition may be improved regarding the baseline period. So, our main focus is to detect alterations relative to baseline. Therefore, special attention should be given at the definition of the baseline period. The baseline interval should be defined taking into consideration two facts: 1) avoid influence from transient, fast-varying events (e.g., sensor noise, acute events) and, 1) slow-varying, seasonal effects (e.g., normal decrease in sleep duration due to summer) that may also influence the baseline calculations.

Identifying that a senior has a specific condition, e.g., geriatric depression, is of great significance since this allows certain therapeutic measures to be taken and triggers constant monitoring of the disease evolution. Given the presence of a disease’s symptomatology, the DSS should quantify the extent of the disease and alert the carer by identifying transitions of health state.

The decision support core components have been developed to estimate current health states. Comparison with previous health states is also performed to examine transitions and to monitor the disease progression. Through timely assessment and identification of such transitions, the component is able to generate alerts for the carer. The results, which were evaluated by our experts (neuropsychologists), demonstrate that the system works satisfactorily in the sense that a high level of accuracy is achieved.

A modified version of the FCM-based depression diagnosis schema was also introduced, where a dynamic selection process intervenes in order to form the final weight matrix. Experiments were conducted, keeping in mind that the primary goal is to achieve accurate transition state findings. Results from both experiments (stable condition or deteriorating) suggest that the proposed methodology has a satisfactory accuracy in cases where either the emotional status of the person remains stable or is deteriorating.

Finally, an FCM-DDNHL approach has been adopted in order to train the FCM model towards predicting and assessing future health risks, e.g., depression. Mild/moderate cases that were wrongly classified as severe refer to simulated cases where there was an improvement of depression severity. Although, modeling of such transition type among severity states fails to offer even fair reliability, it is of little interest to the doctors, as it represents pretty rare cases and furthermore do not reflect actual patient cases. The rest cases showed pretty accurate results.

The results of all the algorithms used within the proposed framework are promising and suggest that our approach will detect elders either suffering from depressive systems or being at high risk of doing so in the future. Of course, further testing with real-life clinical cases is needed to further confirm this result.

A. Limitations and Future Work

The entire DSS system and its algorithms are based on scenarios developed by experts involved in the USEFIL project. Currently, in this project, there exist no real (senior) sensor data as pilots have not been deployed yet. However, the plan is that over the next few months all system components are integrated together and complete system setups become available for installation in seniors’ homes. This unavailability of real data drove the motivation to initiate the production of synthetic scenarios for DSS training and validation (i.e., pseudo-data). The main goal of this phase is to simulate real cases towards algorithmic development and testing. Their performance was hypothesized to remain high when processing either simulated or real data by employing an exhaustive search for patterns that are likely (frequently or rarely) to occur during the pilots.
However, it is important to highlight issues that may limit the DSS performance during the pilot phase. These are the variations (artifacts, outliers, sensor malfunction, missing data) that may occur. All these parameters, superimposed on the inherent complexity of human behavior, increase the variability of the data obtained. Aiming to deal with this problem, synthetic patterns were contaminated with noise, which was modeled as a Gaussian statistical process with varying mean values and standard deviations. In addition to the “filtering” taking place during the data fusion process, training the algorithms with a varying degree of noise is expected to enhance the system’s robustness. Finally, there is the case of the temporal lack of sensors due to malfunction or bad use of the equipment. This situation is highly possible to occur and should be considered during the system development. Alternative approaches can be adopted in order to deal with this situation: the DSS can identify, based on previously obtained data, the system’s behavior in terms of its dominant pattern and its dynamics. Then, a data imputation method may take place, similar to the ones reported in [36].

Another issue has to do with the approach followed within the trend analysis component. More specifically, the methodology developed, calculates trends based only to a single parameter. However, most symptoms in the elderly are much more complex and rely to multifactorial information [37]. For example, insomnia/hypersomnia incidents may be characterized in terms of several parameters such as sleep duration, sleep latency, sleep efficiency, increased awakening after sleep onset, multiple long-wake, etc.). In order to extend the proposed analysis, we aim to follow certain steps: the single variable (sleep duration time series) would be extended by a multivariate feature vector which would be consisted of N1 features (sleep duration, latency, number of sleep intervals) and N2 instances. Then, (1) and (2) described in Section IV-A are performed among vectors and not single variables. Instead of standard deviation, a radius value is defined as parameter and distances among feature vectors are then computed.

VIII. CONCLUSION

In conclusion, it is our belief that the proposed decision support framework has the capacity to accurately evaluate the progression of the seniors’ depressive symptoms and to alert carers, by providing them with useful information for adjusting the patients’ treatment accordingly.

Evaluation of the proposed methodology showed that our approach has a sufficient potential which may be further exploited to identify health risks and to classify seniors into different categories according to their risk levels of becoming diseased. We have already partially applied the proposed framework to other health aspects of the seniors, e.g., activities of daily living monitoring and identification of neurocognitive disease. Still, we expect to gather data from pilots that should start in the near future. Therefore, we will have the opportunity to test the proposed framework under real-life settings and evaluate them in terms of seniors’ quality of life enhancement.


Antonis S. Billis received the Diploma degree in electrical and computer engineering and the M.Sc. degree in medical informatics, both from Aristotle University of Thessaloniki, Thessaloniki, Greece, in 2007 and 2011, respectively. He also received the Psycho degree in business administration and management from the University of Macedonia, Macedonia, Greece. He is currently working toward the Ph.D. degree in gerontology and works with the Laboratory of Medical Physics, Medical School, Aristotle University of Thessaloniki.

His current research interests include medical decision support systems, ambient assisted living technologies, exergaming, and cloud computing.

Mr. Billis has been a Member of the technical chamber of Greece since November 2007.

Christos A. Frantzidis received the Diploma degree in electrical and computer engineering and the M.Sc. degree in medical informatics both from Aristotle University of Thessaloniki (AUTH), Thessaloniki, Greece, in 2006 and 2008, respectively. He is currently working toward the Ph.D. degree in applied neuroscience and works with the Laboratory of Medical Physics, Medical School, AUTH.

His current research interests include affective and neuro-physiological computing, neuro-physiological evaluation of cognitive and physical interventions targeted on elderly populations and medical expert systems.

Mariana S. Tsatali received the Bachelor’s degree from the Department of Psychology, Aristotle University of Thessaloniki (AUTH), Thessaloniki, Greece, in 2004, and the M.Sc. degree from the University of Ioannina, Ioannina, Greece, in 2011. She is currently working toward the Ph.D. degree in the Department of Psychology, University of Sheffield, Sheffield, U.K.

She currently works in Greek Alzheimer Association. Her current research interests include neuropsychology, dementia, nonpharmacological interventions, mood disorders, Parkinson’s disease and emotional function, scales’ validation, and chronic pain.

Ms. Tsatali has been a Member of American Psychological Association (APA Psyc Net) since 2010.

Anthoula C. Tsolaki received the Diploma degree in medicine from the Medical School of Aristotle University of Thessaloniki, Thessaloniki, Greece, in 2008. She is currently working toward the Ph.D. degree.

After receiving the Diploma degree, she had worked in the Greek Association of Alzheimer’s Disease and Related Disorders from 2009 to 2013. She is currently working in Information Technology Institute, Centre for Research and Technology, Hellas, Greece, about risk factor genes for Alzheimer’s Disease and nonpharmaceutical interventions and collaborates with the Laboratory of Medical Physics, Medical School, AUTH, on gerontechnology projects (USEFIL, DISCOVER, LLC). Her main research interest includes neurodegenerative diseases.

Panagiotis D. Bamidis received the Diploma degree in physics from the Aristotle University of Thessaloniki (AUTH), Thessaloniki, Greece, in 1990, the M.Sc. (with distinction) degree in medical physics from the University of Surrey, Guildford, U.K., in 1992, and the Ph.D. degree in bioelectromagnetic brain function analysis and imaging from the Open University, Milton Keynes, U.K., in 1996.

He is currently an Assistant Professor in the Laboratory of Medical Physics, Medical School, AUTH. His research interests include health information management, affective and physiological computing and human-computer interaction, (bio)medical informatics with emphasis on neurophysiological sensing and ambient assisted living, collaborative e-learning, content sharing and repurposing, and medical education informatics.
Q1. Author: Table III is not cited in the text. Please check and cite at an appropriate place in the text.

Q2. Author: Please provide the complete page range in Ref. [8].

Q3. Author: Ref. [38] is not cited in the text. Please check and cite at an appropriate place in the text.

Q4. Author: Please provide the location of the institution where the author “Anthoula C. Tsolaki” is currently working toward the Ph.D. degree.