Social Activity Modelling and Multimodal Coaching for Active Aging

Yordan Dimitrov
jordandim@bilsp.org
Balkan Institute for Labour and Social Policy (BILSP)
Sofia, Bulgaria

Zlatka Gospodinova
BILSP
Sofia, Bulgaria
zlatka@bilsp.org

Richard Wheeler
BILSP
Edinburgh, United Kingdom
rwprivate@gmail.com

Martin Žnidaršič
Institut Jožef Stefan (IJS)
Ljubljana, Slovenia
martin.znidarsic@ijs.si

Bernard Ženko
IJS
Ljubljana, Slovenia
bernard.zenko@ijs.si

Vera Veleva
BILSP
Sofia, Bulgaria
vera.veleva@bilsp-pc.org

Nadejda Miteva
BILSP
Sofia, Bulgaria
n.miteva@bilsp-pc.org

ABSTRACT

Social isolation is an important determinant of elderly people's health and well-being. Modern technologies could be a powerful ally in combating social isolation. However, instead of replacing human relationships they should help build them within a person's most natural social circles. This paper presents a framework for development of a technological coaching solution that can safeguard or even boost the everyday social life of the elderly. The modus operandi of this system spans from unobtrusive data collection through data processing and situation assessment of social behaviour, to selection and rendering of the most appropriate coaching actions to the elderly person including through members of their social circles. The assessment and decision-making process also integrates three important groups of external factors which influence the solution. These are: (i) personal profiles of the elderly and those members of the social circles who participate in the coaching process; (ii) objective external environment and (iii) the quality of the coaching actions. The latter is a crucial element of the system's learning abilities.

CCS CONCEPTS

• **Human-centered computing** → **User models**; • **Information systems** → *Personalization*; Recommender systems; • **Social and professional topics** → Seniors.

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KEYWORDS

social activity modelling, personalised coaching, multi-criteria decision modelling, social circles, well-being, healthy ageing, active ageing

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1 INTRODUCTION

This paper focuses on the problem of elderly people's social isolation, as well as on the development of a user-friendly technological coaching system that activates the individuals within the elderly's most natural social circles such as families, friends, neighbours, communities, etc. The work presented in this paper represents a part of the research activities in the scope of the H2020 project Supporting Active Ageing through Multimodal coaching (SAAM)[1].

One of the main distinctive features of SAAM is the focus on keeping ageing people at home rather than transitioning them to care institutions by coaching them with the help of innovative technologies and their nearby social circles. The coaching system in SAAM can be represented as a pipeline of information spaning from sensors through data transformation, assessment and decision models, to coaching devices and interfaces for primary users (PUs) and their social circles.

Sensor readings mostly originate from unobtrusive sensors, such as an environmental sensor, localisation device and smart power meter that are placed in the home environment of the PU and from sensors on a smart mobile phone and a wearable sensing device.

[1] https://saam2020.eu/

Raw sensor readings get transformed by standard feature construction methods into so-called 'features' that are used for data-based description of a given situation or context.

These features and other relevant data (external factors which include, for example, weather reports) are used as criteria in a cascade of three kinds of models: the situation model, coaching action model, and the action rendering model. The aim of the situation model is to assess the social activity context of a particular PU, based on relevant (and available) criteria that describe the situation. Once the social activity is assessed, the second model – coaching action model – is activated. It is used to select a suitable coaching action based on the value of the situation assessment and relevant external factors (such as user's personal profile information). The result of this model is a selected persuasive approach for the coaching action, which is the main input to the coaching rendering model. The latter selects a suitable rendering modality based on selected persuasive approaches and other relevant inputs. Rendering of the coaching simply means the way in which the coaching action will be actuated – what means and interfaces. For example, a coaching action 'suggest a walk outside' could be rendered through several modalities, such as an in-app message, a notification on the smartphone screen, specific audio, visual or tactile nudge, or other. The coaching suggestion is then rendered through a corresponding coaching interface. The coaching interface is in most cases realised through an electronic device. In addition, in SAAM, the coaching actions are also realised through people who are supporting the PU and whom we denote as social circles or secondary users (SU). In some sense, the interface is extended by the SUs. An important aim of our work is to enable and then study and personalise an array of modalities for coaching: from textual, audio, tactile and visual interfaces on wearable and stationary devices to various social circle actions (calls, visits, etc.), which are considered particularly important and interesting for the targeted problem domain.

Thus, coaching actions are the result of situation assessments and represent (i) selected suggestions and/or other persuasive approaches (ii) rendered through a selected modality (iii) targeted at improving PU's connectedness with their social circles. The three models used in the information pipeline are mainly based on expert knowledge, with some parts, such as some of the parameters, also estimated from available data with statistical and machine learning techniques. For modelling and formalisation of expert knowledge we use the DEX methodology [4].

In Section 2, we present some work related to the topic. The concepts that affect the social activity and the corresponding coaching actions are presented in Section 3, with other relevant factors external to the situation model (external factors) feeding in the coaching model discussed in Section 4. Section 5 provides conclusions and plans for further work.

2 RELATED WORK

2.1 Loneliness, social isolation and living alone

The problem of elderly isolation and loneliness has been extensively studied. Loneliness, isolation, and living alone are studied separately [23] and distinction has been made between social disconnectedness and perceived isolation [10].

A review of a number of studies in Britain from year 2000 showed the prevalence of loneliness among the elderly somewhere between 7% and 16% (likely understated due to self-reporting) [13]. A more recent survey in Scotland found some evidence that adults in midlife and the 'oldest old' are at increased risk of loneliness [21]. The shrinking social networks of adults very likely lead to social isolation, which in turn can pose a greater risk for all-cause mortality, increased morbidity, depression, and cognitive decline [9].

A review and critical analysis of scientific literature finds a positive contribution of having more than one type of relationship (e.g. simultaneous friendship and family relationships) to the quality of life and well-being of elderly persons [12].

There are a number of projects aiming at improving the quality of life for older people[2], including those tackling cognitive decline[3]. Work closer to that of SAAM utilise multimodal systems. This is the case of the EMPATHIC project[4], which aims at creating a virtual coach with machine/deep learning capabilities and emotions humans can read to improve independent healthy life years of the elderly [6]. It will provide intelligent coaching based on a database holding social, medical and administrative history information on users. SAAM, on the contrary, is designed to provide coaching for active ageing with almost no explicit user input/attention load. For elderly not familiar with the new technologies it will be almost completely unobtrusive, with even the coaching being rendered to the secondary users from the social network. Similar work has been done in the project CARE [16]. The former is a combination of the functionality of a digital image frame and an active recommender mode. Recommendations are chosen based on context information acquired by sensors and a well-being model. This results in making a decision at which point in time what specific activity to suggest. The recommendation mode is triggered by user presence detected in front of the display, and then users receive context-specific recommendations. SAAM has a more comprehensive decision-making model, where coaching is based on personal profile and preferences, external factors and historical data collected by the system. All these will allow the coaching to be rendered when needed and appropriate. The ALFRED[5] project has developed a fully voice controlled interactive virtual butler for older people, offering context-sensitive services related to social inclusion, care, physical exercise and cognitive games. The added value of the SAAM project compared to ALFRED is that it offers several basic modules (domains), for example mobility, activity, sleep and social activity, as well as several advanced modules – dietary, cognitive, emotions, cardiovascular, and emergency. These modules cover a broad spectrum of elderly life and will be able to run individually or jointly. Each of them has a separate pipeline within the system, which allows the system to provide fine-tuned personalised coaching.

2.2 Situation modelling, user profiling and decision making for coaching

The ultimate goal of helping elderly reduce their isolation and improve social activity is achieved through coaching actions. In

[2]http://www.aal-europe.eu/projects-main/
[3]http://www.enrichme.eu/wordpres
[4]http://www.empathic-project.eu/
[5]https://alfred.eu/project/index.html

SAAM, these are a product of situation modelling, including user modelling, coaching modelling, and decision-making processes.

Both kinds of modelling tasks can be tackled with multi-criteria assessment models, for which there exist a number of mature methodologies. The most well-known are Analytical Hierarchical Process (AHP) [18] and Multi-Attribute Utility Theory (MAUT) [14], but there are many others, among which is also DEX [3, 4], used in our work.

Recent developments in Ambient Assisted Living (AAL) saw a broad development of tools and methods for computer observation of human activity like sensors, cameras, microphones, and interaction devices [2, 15, 19]. Such observation is integrable with external information and user models (profiles) into coaching (recommender) systems. Since user's perceived isolation may differ from the objective one, models should include user profiles to improve personalisation of the system. Personalisation has been seen as an important facet, especially for coaching systems, due to acceptability and usability issues that are specific for the elderly. Among these are feedback issues with respect to coaching content, timing, amount and rendering [17]. SAAM addresses these through customisation for the user's abilities and preferences ranging from smart phone interfaces adapted to the elderly (including those linkable to modern TVs), and social interactions with caregivers, family or friends.

Personalisation elements can be partly learned by the system and partly entered manually by the user or a person from the user's social support network. Whether learned or not, they should include the user requirements, preferences, abilities and motivations [1], as is the case of SAAM. These are different for each user and may be either dynamic or (relatively) static, depending on the user's context. The system will learn the user's preferences and autonomously select an optimal interaction pathway for a given situation using innovative persuasive interaction design strategies. In order to detect and respond to human activity, a context model describing the environment, its users and their activities also should be developed. Some work has already been done on context modelling using situation models [5]. The article describes development of an intelligible framework for supervised and unsupervised discovery and learning of situations from multimodal observation using a situation model. This model is based on and motivated by the perception of human activity. A method for integrating user preferences into the situation model is also proposed, based on user feedback which permits to personalise the constructed situation model.

SAAM, in addition to such a situation model, proposes a coaching model and rendering model. These models are rule-based and executed consecutively, in order to ensure a high level of personalisation of the output coaching actions.

3 SOCIAL ACTIVITY MODEL

The research review shows that the healthy and active aging is determined by key factors such as loneliness and feelings of loneliness [13], social support [22], social activity levels and sense of social fulfillment [10], social and family relationships [23], and the like.

In the social activity model, we consider social isolation of an elderly person as the main problem and then integrate most of the aforementioned factors in a single hierarchy model. The ultimate goal of this model is to assess the overall social activity of an elderly person and some underlying concepts, which are all used as inputs in another (following) model for selection of suitable coaching actions. The aim of this second model is to select and suggest coaching actions to the elderly or their social circles based on a situational analysis of their isolation peculiarities and relevant contextual and personal information. The coaching suggestions are then rendered through the third model (rendering model) that chooses the way in which the coaching suggestion is delivered to the user (see SAAM information pipeline for social activity coaching in Figure 1).

Figure 1: Information pipeline for social activity coaching in SAAM

Whether a coaching suggestion rendered through the system is taken up and completed by the users depends on their free will and the trust they have in the system. The latter is largely determined by the privacy preserving capabilities of the system. In this respect, we follow state-of-the-art approaches towards privacy and confidentiality, including but not only reducing to a minimum the amount and type of data collected. The system itself follows the privacy-by-default and privacy-by-design principles. Among its privacy preserving features are newly developed integration algorithms and simple on-off switches for user profile privacy settings, among others.

3.1 Hierarchical structure

The first step in developing a social activity model is to identify the main problem we want to address and then to break it down hierarchically into its components. With regard to the hierarchical structure, we considered two possible ways of building the internal logic of the model. The first one was to build upon isolation from different social circles such as family, friends, neighbours, professional service providers, communities, work providers, etc. The second possibility was to build the model of isolation from various types of social activities including calling, chatting, visiting, meetings outside home, attending formal or informal events, participating in work activities, etc. Based on the main idea of the SAAM project – aimed at activating elderly people within their social circles relationships – we set up our hierarchy around the isolation from the different social circles.

We define three types of isolation at the second level. These are: isolation from family and friends; isolation from community life; and undefined isolation. The latter covers situations in which social circles cannot be identified. Each of these types of isolation is assessed at the third level of the hierarchical model through intensity of calls, chats/talks, visits, meetings outside home, attendance of formal or informal events, and participation in work activities. The resulting situational analysis is based on a series of measurements specified for each third level element (see Figure 2).

The coaching action model takes into consideration three groups of external factors that influence the final results and decisions.

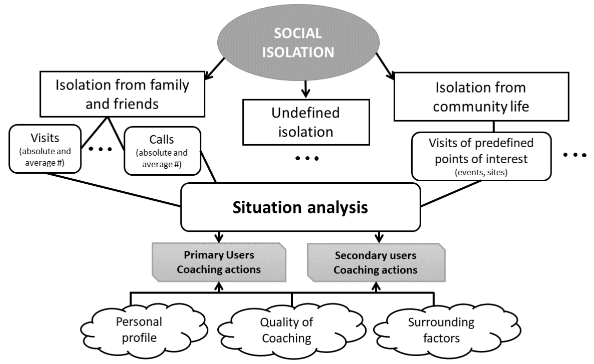

Figure 2: Partial representation of hierarchical model of elderly social isolation

These are (i) the personal profile of the PUs, (ii) the surrounding factors from the PUs' enivorment relevant to their social activity and (iii) the quality of coaching actions previously recommended to the elderly by the system (see Section 4.3).

The situation assessment provides input for further recommendations for personalised coaching to be aimed either to the PU (e.g., 'go and meet your neighbour'), or to SUs but with the ultimate goal of activating the PU (e.g., 'invite your friend to go out').

3.2 Multi-criteria decision modelling

In our system, we apply DEX as a multi-criteria decision modelling methodology that is well established in practice and is supported by freely available tools, primarily by DEXi[6]. Similarly, as in many other methodologies of this kind (such as AHP for example), its models have a hierarchical structure of concepts. The lowest level concepts are inputs for the model, which get hierarchically aggregated into higher-level concepts up to the outputs, which usually represent assessments of decision options. A distinctive characteristic of DEX is its focus on qualitative modelling in which the inputs to the model are qualitative values and the value functions (the functions used for aggregation of criteria into higher level ones) are rule-based, usually represented in tabular form. Its qualitative nature allows the models to be transparent, which is particularly useful in situations in which the operation of the model must lend itself to human understanding. However, this can also be a limitation in situations in which relationships among the criteria are naturally numerical (summations, averages, etc.). Such relationships usually occur at the lower levels of models, thus, they are commonly left out of the main model and separately computed as inputs. If a direct inclusion of such concepts is necessary or beneficial, it can be done by using specific DEX methodology extensions [25, 26].

3.3 Situation Assessment

The social activity situation assessment model considers two main scenarios. The first one represents the case when a specific social circle could not be identified for a given PU. In this case 'undefined isolation' levels are measured with a combination of proxy criteria, such as 'overall calls' units and duration, 'overall visits' units and duration; units of 'time spent outside'; and 'duration of speech', compared for a specific period of time. In this scenario, patterns of the user's interaction with the outer world and behavioural changes can also be detected, if occurring, for more general coaching.

In the second scenario, the PU's social circle can be identified and is also engaged in the system through the SAAM mobile application. In this case, the participating members of the social circle are considered as SUs by the system. This allows the system to obtain more detailed information on the social status of the elderly by groups of actors from their surroundings, which allows the coaching actions to be more appropriate. Defined isolation situations include isolation from family and friends and isolation from community life. In the case of isolation from family and friends, the system tries to assess if a given lack of interaction is focused on a specific person/group of persons from the social circle of the PU. The criteria, building the model of 'undefined isolation', such as 'calls', are then used with additional metadata of the SUs.

Identifying the social circle and internalising them in the model allows for more concrete situational criteria to be elaborated, such as detecting if the PU is in the company of a specific SU and establishing their interaction patterns. Potential proxies for detecting such a situation are pairing of mobile phones through Bluetooth and potential detection of the PU at addresses of family and friends through GPS tracking. The latter is privacy intrusive, but an important tool for measuring the social behaviour of the elderly outside their home, because it avoids 'attention theft'. Another advantage is the automatic detection of community points of interest or other social engagements spots.

The GPS tracking could also be linked with calendars of events or action reminders and be used to detect whether the PU is acting upon the specific coaching actions, such as self-reminders to go to specific places. For this purpose, the addresses of social points of interest should be tagged manually or be constantly registered in an automated way for the system to be able to learn if a given location is random, sporadic or constant. All these options that include long-term continuous personal GPS tracking are a subject of legal, ethical and user requirements analyses before being put to use.

Value scales of the situation criteria depend on the type and level of each criterion. The high level value scales are per group of the three main isolation situations – undefined, from family and friends, and from community life. At this level, the model uses 5-point Likert scales, ranging from very low to very high. As the model breaks down into sub-criteria, the value scales and computational strategies diverge from one to another.

For example, if the criterion 'calls' is examined, its indicators are 'total duration in minutes', 'number of units per period' and 'time of the day' they take place for a specific SU ID or in general (if no SU is registered in the system). The input data is extracted from the smartphone calls metadata of the PU for undefined isolation, or from a specially developed VOIP system that runs on the mobile through a native application (VOIP will be able to tag calls with PU and SU ID and provide the needed input for the situation and coaching model algorithms). For certain indicators, such as assessing the 'number of units per period', the function consists of a given absolute threshold and adds percentage change for the given period unit. For other indicators, such as 'time of the day' the model has two

[6]http://kt.ijs.si/MarkoBohanec/dexi.html

values: normal and abnormal, considering the defined timeframes. The last indicator of 'calls' takes only the percentage change of one period, compared with another.

The technology behind the situational assessment of the social activity model consists of several indoor sensors (smart power meter, ultrawideband localisation sensor, microphone and environmental sensor for temperature, pressure and lighting), a personal wearable sensor (with gyroscope, accelerometer, pressure, temperature, custom features) and a smart mobile phone with Android OS that is constantly running SAAM application, Bluetooth, potentially GPS tracking and a custom VOIP application through which calls should pass. This unobtrusive hardware and software collects the input data needed for running the assessment and coaching models. Data input for the social assessment model will be mainly based on smartphone general metadata (number, duration of calls and messages, localisation), from smartphones running the SAAM app that gather the needed data (detecting pairing of users' running the SAAM app, collecting statistics from the app's VOIP, push notifications for taken social activity actions from the app calendar), and from home sensors (e.g. Matrix creator for temperature, UWB localisation sensors for detecting PU presence in home or outside). The rules governing the results from the situation assessment module for the social activity domain are currently being developed by the research team together with domain experts and will also integrate user profile goals and constraints. The models will be tested in controlled environments to validate their accuracy by limiting false positives. Privacy and security for the complete system will be ensured through several already identifies requirements: machine learning will be run on parsed and anonymised data; there will be no direct exposure of databases to end users (PUs and SUs); the end users will have access to data only through the SAAM application which will require authentication; the whole infrastructure will be subject to extensive performance availability, confidentiality and integrity monitoring; all privileged access to the infrastructure will be highly controlled; all reporting capabilities for the system will be ensured by utilising very strict role-based access models to ensure relevant data is delivered only following need-to-know-need-to-have principles.

3.4 Coaching Actions

As mentioned, coaching actions are selected suggestions and/or other persuasive approaches rendered through a selected modality targeted at improving PU's connectedness with their social circles. Coaching action selection is informed by the social activity measurements during the situation assessment stage. The calculated output of the situation assessment stage is represented as a single value from a 5-point Likert scale with a range from 'very low' to 'very high'. The output triggers the coaching system to initiate a coaching action or not depending on whether the PU is socially active enough[7].

Should there be a decision for coaching action, then the coaching system refers to a set of criteria that are part of the external factors for coaching. They influence the coaching action decision in two ways – as enablers and restrictors (vetoes)[8]. As enablers, they influence the coaching action decision by dynamically changing the weights attributed to individual coaching actions. As vetoes, they impede the execution of a coaching action (by rendering a 'no action' suggestion). For all non-vetoed coaching actions, the coaching system decides which one to suggest to the PU or SU. Coaching action options depend on the persuasive approach and may include: suggest going out, suggest event, send positive message, suggest call, suggest visit. The selected option is then rendered depending on PU's and SU's preferences as defined in the rendering model.

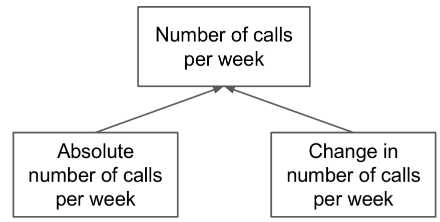

Figure 3: Hierarchical relation of concepts *Number of calls per week, Absolute number of calls per week* and *Change in number of calls per week.*

3.5 Aggregation Rules

Aggregation of concepts into higher level ones, for example aggregation of *overall calls*, *overall visits*, *time spent outside* and *duration of speech* into *undefined isolation* as explained in Section 3.3, is defined with qualitative rule-based functions, which are called value functions or aggregation functions of the model. In DEX, these functions are a series of if-then rules which define the value of the higher-level concept for every combination of the values of its inputs (concepts that aggregate into it). This allows for transparent modelling and enables modelling of various phenomena including highly non-linear relationships, veto values, etc.

Let us illustrate qualitative value functions on a small example that is sketched in Figure 3, which shows a breakdown of the concept *overall calls*, namely the *Number of calls per week*. Despite its name, this is not a direct input, but a somewhat more complicated concept for assessing the weekly number of calls both absolutely and in relative terms. These are represented as *Absolute number of calls per week*, which can take values low, average or high and *Change in number of calls per week*, which can have values *decrease*, *stable* or *increase*. The rationale of this aggregation is to only encode extremely low (<2) or high (>14) absolute values as *low* and *high*. In between, we consider relative changes. The qualitative value function is shown in Table 1, where for each combination of the values of lower-level concepts, we can see the corresponding value of the *Number of calls per week*. In fact, this function implements a kind of veto function for specific values of the *Absolute number of calls per week*. Namely, if these have the value *low*, the aggregate is also always *low*, despite the value of the other criterion. The same

[7]Note: The decision not to initiate a coaching action is overridden, if there is a social engagement goal set, but not met by the PU.

[8]Note: Enabling and restricting can also be realised in the aggregation functions of the coaching action model, not only in the scope of here explained post-processing of the model's coaching action decision.

holds when the value is *high*. If the value is *average*, on the other hand, the relative concept prevails.

Table 1: Exemplary qualitative aggregation function for the concept *Number of calls per week*.

Absolute...	Change...	Number...
low	decrease	low
average	decrease	low
high	decrease	high
low	stable	low
average	stable	medium
high	stable	high
low	increase	low
average	increase	high
high	increase	high

Functions of this kind are to be set for all the aggregations in our three models.

4 EXTERNAL FACTORS

Social activity modelling aimed at social coaching needs to take into account a multitude of external factors for the PU, in addition to situation measurements per se. This is done to avoid irrelevant coaching action suggestions [11]. We divide external factors into three discrete groups, namely personal profile factors, surrounding factors, and coaching action quality monitoring. These additional factors are flexible enough to be enriched over time, depending on the PU's preferences for information sharing, as well as theoretical developments in the AAL field. Most personal profile and external factors are introduced in the model manually when creating PU's virtual profile in the coaching system. After the initial profile setup, the majority of personalisation factors are subject to the system's learning abilities, which can take into account also the quality monitoring data of the coaching system.

4.1 Personal Profile

Personal profile factors encompass a vast group of a person's circumstances defining their life as a 'social animal' (e.g. [7]). To ease the modelling process, we break them down into four subgroups, depending on the extent to which the subgroups are linked to the PU's interaction with the coaching system.

First, we take into account personal factors that are contextual. Contextual factors are relatively static and are independent of the coaching system. They are the broadest subgroup and include the person's health, family and friends, existing social obligations, and personal interests. They require manual input at the time of the profile setup and most require manual update over at defined intervals.

Secondly, we differentiate a subgroup of social availability factors that directly affect both social activity measurements and coaching action selection. Social availability factors are mostly static and depend on the coaching system. In this subgroup, we include the availability of SUs registered in SAAM for the PU and these SUs' attributes. SUs' attributes resemble those of PU's personal profile, they are gathered and manually input during the initial SU profile setup in the coaching system and some of them are subject to estimation and update through the system's learning abilities over time. In addition, they include normal spatial distance to PU and SU's personal calendar.

Third, we define a subgroup that includes secondary personal profile elements characterising the relationship between the PU and SAAM (PU – SAAM relationship). This relationship is dynamic and depends on the coaching system. In this group, we include the social engagement goals, defined as an improvement in social activity measurements agreed with the PU and rewarded if met, that the PU sets for herself in SAAM and the PU's coaching action rendering preferences. Goals and rendering preferences are manually input at the time of profile setup and can be updated later if necessary. Some goals and preferences might be automatically changed by the system based on AI methods, which is a topic of further research.

Fourth, in an ideal situation the coaching system would correctly assess the emotional state of the PU immediately after a social interaction. This assessment would then be aggregated into a long-term measurement defined as social emotion. Whether we talk about social anxiety or exhilaration, emotion can significantly affect social activity [8, 20]. This is why it needs to be taken into account on its own. Emotional assessment, however, is a technological challenge, so long-term social emotion assessment at present remains in the social activity model only theoretically. In practice, in the scope of SAAM it will be estimated only based on measurements from a limited number of one-on-one interactions at regular time intervals. The emotional assessment will be subject to the system's long-term learning.

4.2 Surrounding Factors

Surrounding factors are those environmental factors in the life of the PU, which tend to influence their social interactions the most. In this group, we distinguish between weather conditions, home location and characteristics, neighbourhood characteristics, transport availability, including PU's car possession, available GPS locations outside of the home of the PU (community points of interest, CPIs), as well as local and national events calendars. Most surrounding factors are dynamic and subject to system's learning (mostly environmental factors), while some of them are more static and input is done at profile setup (related to PU's residence and surrounding infrastructure). A prerequisite for the former is to integrate the coaching system with weather forecasts, national events calendars and national official alert systems platforms.

4.3 Monitoring and Assessment of Coaching Actions

Quality of the coaching actions is a factor that should influence the selection and recommendation of coaching actions. It is a dynamic variable whose values change in time. It is an important element of SAAM's learning abilities that takes into account a single user's experiences and behaviour.

The quality of a coaching action is being measured through two main groups of indicators – for effectiveness and efficiency.

The effectiveness shows the rate of actions being followed by the users versus those not accepted (e.g., the system has recommended the user to 'call a friend' 10 times and she did it just 3 times).

Efficiency measures the impact of certain implemented actions on specific indicators (e.g. visiting local pensioners club two times per week has led to an increase in the number of visits at the PU's home).

The efficiency indicators could be either single (e.g., number of outgoing calls per day) or a cumulative index (SA - Social Activity) covering different variables (e.g. overall index for social activation including calls, visits, participation in events, work, etc.).

Then, the impact of each coaching action could be measured for instance through linear regression models, when enough data are available on user's behaviour and personalised results. The choice of the exact type of the regression model can be refined after ex-post quality evaluation of the monitoring and assessment model results. For that purpose, social isolation can be measured through some qualitative and quantitative user surveys [24] and compared with the results produced by SAAM system monitoring and evaluation model.

Efficiency of the coaching actions can be measured through other objective or subjective proxies. The former is counting the repeatability of certain coaching actions without system reminders. This can be easily implemented within the SAAM basic system. The subjective proxies are more complex and difficult to implement. Such are indicators of the emotional state of the elderly during or immediately after the implementation of certain coaching actions. However, the latter requires further research and technical integration.

For each of the observed variables, exact measurement periods should be defined. For instance, the changes in overall SA index could be measured per week, month, or other.

Furthermore, calculating the overall quality of coaching actions requires specifying some preferences between effectiveness and efficiency. Then, the quality result for each coaching action can be calculated more accurately.

This way, the described system learning effect is based exclusively on personalised data. In the future the learning effects could be derived from the experience of many users taking into consideration the homogeneity and heterogeneity of the groups' profiles.

5 CONCLUSION AND FURTHER WORK

This paper describes a basic technological system that after being operationalised, will assist elderly people in maintaining healthy social activity to combat isolation and promote independent living. The system merits are in the user-friendly methods for gathering data on the social activities of elderly users, and then rendering coaching suggestions built on real human relationships. The main players are the elderly and members of their natural social circles, such as family and friends, neighbours, and professional service providers. An important prerequisite for keeping the system unobtrusive and operational is that all actors to agree to participate and all legal and ethical principles are understood and abided by. The selection of coaching actions is based on situational assessment of the person's social isolation, the personal profile of the user, the objective external environment and the quality of the coaching actions in terms of their effectiveness and efficiency. For data collection purposes, the initial input to the system consists of some preliminary data, which is manually entered and can be revised if needed. Other types of data are collected automatically through sensors and tracking tools. In a later stage, the system will begin conducting self-assessment of the coaching actions that it suggests to the users based on the individual's performance in the time period of coaching. The system's learning abilities are subject to future research and development opportunities. The first is the opportunity to raise system's learning potential based on the cumulative performance results of all system users. The second opportunity is related to the implementation of group profiling instead of the currently used personal profiles. Another opportunity is to complement the overall quality assessment of the coaching actions with measurements of changes in the emotional state of users, which will be based on advanced data collection technologies, which are also a research subject in scope of the SAAM project.

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