Conceptualization of a Personalized eCoach for Wellness Promotion

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ABSTRACT
Evidence-based health promotion programs implement clinical practice guidelines built upon results of clinical trials with a definite number of participants, collected during a specific period of time. Wearable technologies allow for continuous observation of wellness parameters of multiple citizens, combined with monitoring of activities and context parameters involved in citizens' wellness. A statistical inference model can describe the relation between multidimensional activities and context parameters, the wellness of an individual and a comparable reference group, utilizing machine learning techniques and knowledge from continuous observations of multiple citizens.

This paper presents a holistic concept of a coach system, namely eCoach, that combines specialized medical evidence available from randomized control trials, with individual and reference knowledge to create and reinforce wellness-based recommendations. The eCoach adapts these recommendations in a continuous personalized coaching dialog addressing citizen's needs and preferences.

Author Keywords
eCoach; holistic observation; personalized recommendations; reinforcement; HCI personalization; machine learning; Big Data; AI

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INTRODUCTION
The expected inversion of the age pyramid [37] comes along with an increase of functional limitations, disabilities, and demand for long-term care of chronic diseases, challenging current health and care systems [7]. For the professional healthcare sector the higher demands on long-term care and the general economic pressure to control health care expenditures means a rising requirement for efficient utilization of health information technologies and increased cross-border collaboration. Self-monitoring and self-management of fitness parameters have become popular because of the provided information about individual health and wellness status. There is also an increasing amount of data produced by younger generations born into the "Internet Age". This particular group of technology users is used to smartphones, wearable Internet-of-Things (IoT) devices and cloud-services, which allow them to use data associated to their life-style. Both trends, a socio-economic need for a stronger citizen involvement in management of their health and disease, and readiness for understanding and control of their health and lifestyle, raise the demand for personalized wellness promotion. In this line, the health sector provides information to formal and informal healthcare providers and individual healthcare receivers with information about health status, diagnoses and recommendations for interventions. However, there are still various limitations in this flow of information:

- Emerging commercial solutions to collect health, wellness and context related data (e.g. FitBit fitness wristbands, Empatica E4 wristband, Apple Watch and Health App, etc.) typically upload data through non-open cloud services. Such data is not available to formal health and care service providers through services and applications in the public health information systems. Wellness evaluation approaches of these solutions have limited validity [19], and activity and lifestyle recommendations are typically not quality-assured based on clinical evidence.
- Clinical decision support systems (CDSS) have a clinical focus and provide decision support for healthcare professionals. However, these systems do not always include patients in their design which generally hinders

patients and other citizens from understanding and correctly using such systems.

- Telehealth systems for remote patient monitoring (RPM) provide support to patients for assessment and reporting of health parameters. These systems provide remote monitoring support for healthcare professionals with the evaluation of the reported parameters and decision support for the follow-up of patients. However, RPM systems do not generally provide information and recommendations directly to patients.

Artificial Intelligence (AI) enables technological evolutions and innovations in the healthcare sector, that are already utilized in medical research for analysis of clinical data, for support of diagnoses and treatment plans in clinical decision support systems. Potential can also be envisioned in a decentralized provisioning of healthcare, which may have significant advantages, e.g., for the quality of life of home-living elderly people.

In this paper, we propose the conceptualization of a *personalized AI-driven electronic coach (eCoach)* for *health and wellness promotion* (Figure 1). The goal is to provide citizens with personalized information and recommendations for their health and wellness education and self-management through a continuous personalized dialog.

For the purpose of explaining the eCoach, we use the following denotations:

Wellness Status: continuous holistic observation and assessment of functional and physiological wellness parameters, cognitive and mental parameters, social wellbeing parameters and spiritual faith.

Activities: observation and assessment of holistic activities and actions performed by the citizen, as e.g., physical activities, nutrition and medication.

Context: influencing factors, e.g., time, location, environmental conditions, climate and weather conditions.

Recommendations: multimodal recommendations regarding behavioral and contextual aspects to motivate for changes of activities, or to change contextual conditions.

The eCoach will continuously assess citizen's activities and wellness status, and provide personalized recommendations. The AI-driven eCoach determines recommendations from reference knowledge (i.e., from clinical practices guidelines (CPAs), that are based on medical evidence and are turned into computer-interpretable guidelines (CIGs), and from historic and present observations of others), and from reinforced knowledge about optimal activities and interventions for an individual citizen.

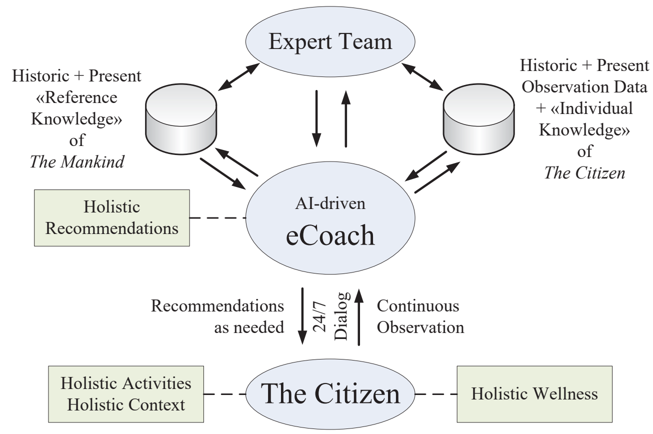

Figure 1: Purpose of the eCoach

The *Expert Team* of medical and healthcare specialists supports the development, training, validation and operation of the eCoach, and receives decision support information about monitored citizens. In the following discussion, we focus mainly on the recommendations provided to citizens as the primary eCoach users. The Research Background following this introduction provides background information related to the proposed eCoach concept from the fields of Human-Computer Interaction (HCI), Holistic Wellness Assessment, Data Collection and Transmission, and Artificial Intelligence (AI) technologies for healthcare and wellness management. The Solution Requirements Outline explains the general approach of the eCoach concept and requirements for the realization, describes the HCI personalization and provides details about the wellness management process from a technological perspective. We also explain main aspects for the realization, validation and evaluation of the eCoach. The Discussion explains advantages of the eCoach at a conceptual level compared to existing solutions, and improvements for eCoach users. We conclude with a summary of the characteristics and advantages of the proposed eCoach.

RESEARCH BACKGROUND

Human-Computer Interaction (HCI)

The development of an eCoach places end-user at the center. Methods such as user-centered design, participatory design or co-design turn end-user into active contributors of the technology design process, evaluation and outcome. The eCoach applies a holistic approach that implies the analysis of four dimensions of the human being: physiological, cognitive, mental and social. Ultimately, the eCoaching outcome will result in customized advises and invitations for action specifically targeting human physical activity, clinical interventions and context. In this regard, time and space are two critical components of the inclusion of a human user. Thus, one of the core elements is the personalization of the coaching. The eCoach should be able to adapt also the type of interaction with each user, appropriate to the personal, technical and clinical circumstances concurrent to the eCoaching process.

Aspects such as usability, accessibility and interaction design are part of the Human-Computer Interaction (HCI) that addresses how users use, access and interact with technology. The usability component will address the ease-of-use of the interface; the accessibility component will address the adaptation of the eCoach to the range of abilities and disabilities of user. Visually disabled users and patients with chronic diseases, for example, present different challenges for designing the interaction, user interface and access to information.

Wellness Assessment

Researchers have described their views on *Wellness* as a "holistic complex concept that is affected by several internal and external factors and parameters". The World Health Organization (WHO) has defined *Wellness* as "the optimal state of health of individuals and groups. There are two main concerns: the realization of the fullest potential of an individual physically, psychologically, socially, spiritually and economically, and the fulfilment of one's role expectations in the family, community, place of worship, workplace and other settings" [33]. *Health* has traditionally focused on the individual in relation to illness status, and also a newer WHO definition of *health* as "physical, mental and social well-being" [6] focusses on the individual's health perception as assessed by questionnaires and its functional and bodily reserves as measured by physical means.

Quality of life has been defined as "individuals' perception of their position in life in the context of the culture and value systems in which they live and in relation to their goals, expectations, standards and concerns" [28]. Compared to other health-related concepts, such as *health quality-of-life* (H-QoL), *wellness* looks at both individual dimensions as well as dimensions of the integration of the individual in its environment. In line with this, Hoyman has described the *human health* as a "multi-dimensional unity, involving the whole person in his total environment", and has suggested a wellness model consisting of four inseparable dimensions: physical fitness/well-being, mental and cognitive health, social well-being, and spiritual faith [15].

To observe and quantify wellness at a single point of time or the change over a period of time by a cohort of sample parameters, Rachele et al. provide an overview of a variety of instruments for the unidimensional and multidimensional measurement and assessment of wellness, along various wellness models [29]. Demiris, Thompson et al. have studied a holistic approach and a framework for the technology enhanced assessment of older adults' wellness [10, 35], informed by Hoyman's wellness model [15]. Study participants expressed the desire to understand their own wellness information more in depth, and showed interest in specific programmatic activities around promoting wellness, and wanted to know what they could specifically do to improve or prevent decline a specific need or area. They found that their framework of informatics based wellness assessment could support a holistic view of older adults' needs, facilitate decision making, links between formal and informal caregiving networks, and could lead to identification of early trends and patterns.

Data Collection and Transmission

Internet of Things (IoT) technologies are applicable to the health sector for the collection and transmission of observation data from citizens' point-of-care (PoC) to a central services infrastructure [14]. Specific solutions have been proposed, e.g. by Paschou et al., for metrics and methods for an efficient data transfer in combination with a Health-IoT [22]. Amin et al. presented a device independent Data Curation Framework (DCF) that accumulated sensory data from multimodal sources in real time [4]. The DCF allowed the creation of a context-rich lifelog as basis for multidimensional insights into user activities and behaviours. This enabled the DCF to support data-driven knowledge-generation, and descriptive and predictive analytics. Rawassizadeh et al. focussed on smartwatches as platform for context sensing and context analysis, and proposed an energy-efficient, generic, integrated framework for continuous sensing and prediction on small wearable devices [30].

Artificial Intelligence (AI) technologies for Healthcare and Wellness Management

The increasing deployment of IoT-systems for the collection and transmission of healthcare-related data in Electronic Health Record (EHR) systems leads to a rapidly expanding amount of data. Converting this *Big Data* into information and knowledge has manifold potential to improve the quality and efficiency of health care delivery [21]. *Big Data* processing expands the capacity to generate new knowledge for the healthcare sector from clinical studies and historic patient journals, and it can help with the dissemination and utilization of the knowledge in the field for diagnostic reasoning by physicians. Clinical decisions often rely on the experience of decision makers to interpret presented information, following an intuitive approach [8]. The individual experience can be extended by a decision support system based on knowledge from historic and long-term continuous monitoring. Such systems can also empower patients by delivering information directly to them (and to citizens in general), allowing them to play a more active role in their personal wellness management.

A key for dealing with the large information sets and hence for the realization of the potential of Big Data is the advances in analytic techniques in Computer Science, especially in machine learning. The analysis of Big Data leads to information and knowledge about the *context* of the citizen, and allows to provide *context-aware* healthcare services [26]. *Context reasoning* (or inferencing) techniques can be classified into supervised learning, unsupervised learning, rules, fuzzy logic, ontological reasoning and probabilistic reasoning [26]. These techniques can be utilized to provide diagnosis support for medical professionals, to dynamically adapt healthcare workflows to patient's condition, and to provide recommendations and decision support information for interventions and behavioral aspects.

The interaction of citizen's wellness with a dynamic contextual environment and multimodal individual activities as considered by the eCoach has analogies with *Reinforcement Learning* [16]. This describes the problem faced by an agent that learns behavior through trial-and-error interactions with a dynamic environment. The three most important distinguishing features of the reinforcement learning problem are being a closed-loop in an essential way, not having direct instructions as to what actions to take, and where the consequences of actions, including reward signals, play out over extended time periods.

Existing *Clinical Decision Support Systems (CDSS)* are computer-based decision-making systems to analyze and diagnose medical problems and diseases, and aid in treatment guidelines [2, 39]. Methods have been developed and validated for representation of medical knowledge and inference under uncertainties [18]. An important basis for computer-assisted diagnosis (CAD) and decision support for treatment plan are computer-interpretable guidelines (CIGs) [25]. CIGs are formalized clinical practice guidelines (CPGs). CDSSs are generally not designed for real-time evaluation of observations, diagnosis and decision support recommendation in telehealth settings for remote monitoring and for end-user coaching.

Bayesian Network Modelling is an AI-technology which is in particular useful for the evaluation and assessment of heterogeneous observations with uncertain and complex dependencies as required for the eCoach concept. It has been validated for the reasoning of data from sensors and humans in pervasive health monitoring settings [24, 38]. Furthermore, technologies for the recognition of activities of daily living (ADLs) and the corresponding wellness assessment have been presented [34].

Deep Information Understanding and Reasoning is another AI-technology, that has validated advantages for the mining of knowledge from structured and unstructured data records, in particular from medical records [1]. The generation of reference knowledge and the multidimensional classification of the information is an essential prerequisite for the determination of personalized recommendations by the eCoach.

Recommender Systems cover content-based, collaborative, or hybrid recommendation methods [3]. The consideration of user preferences in content-based recommendations and of recommendations for other people with a similar profile in collaborative recommendations presents similarities with the eCoach goals.

Existing solutions for wellness promotion

Mining Minds is a novel digital framework for personalized healthcare and wellness support [5]. It models daily life events using heterogeneous input sources and provides personalized services to enhance human life style through customized and personalized user interfaces capturing user preferences, platform usage and user's contextual information. It aims for user engagement and provides services in terms of a virtual caregiver.

The cognitive computing system *Watson* from IBM has proven strengths in natural language processing and the learning from structured and unstructured data. This is used for example in clinical research to determine knowledge for diagnosis and treatment support from the automated analysis of large amounts of unstructured health records. A number of case studies illustrate how Watson is used for support of healthcare services provisioning, in particular in cancer treatment [11, 19].

SOLUTION REQUIREMENTS OUTLINE

We will identify the main requirements of the eCoach along the description of a user scenario.

User Scenario: Wellness Management

The eCoach will involve citizens in their management of wellness and disease, with positive impacts on their perceived quality-of-life. Following, we present a description of how the health management of an older patient would look like without an eCoach.

Biography: Anna Katarina (AK) is an 80-year-old lady who lives in a small town in a Scandinavian country. She widowed 2 years ago. AK has one daughter who lives 600km away.

Health condition: AK was recently diagnosed with chronic obstructive pulmonary disease (COPD), and with potential diabetes risk. AK has also sporadic episodes of mild depression. In addition, she has started to have some random memory losses although she has not told anybody, yet, because she is unsure whether she suffers from them.

Interaction with Technology: AK has had to learn how to daily check her glucose and oxygen saturation (SpO_2) levels, pulse, and other related measures to monitor her health.

Interaction with National Health System: AK visits her general practitioner once a month and the hospital once a year. The distance from AK's home to the nearest health care facility in the municipality is around 90 minutes by car, and around 150 to the hospital.

Traditional Statuses Assessment: AK's health status will be intermittently assessed based on the frequency of established visits to her GP and hospital, unless otherwise indicated by emergency episodes. Cognitive and mental status will be established by default as sufficient for her age and conditions, unless otherwise reported by specialized or primary health services. Social condition will be only intermittently assessed by municipal services.

Conceptualization of eCoach

The proposed conceptualization outlines *How* to personalize the coaching HCI, the observation and analysis process for the determination of *What* to coach, and the *validation approach* of the eCoach in the field.

The eCoach continuously estimates wellness trends and risks by utilizing medical evidence as well as historic knowledge about the impacts of activities and context parameters on the individual citizen and on a reference group. It determines the best activities and context changes to achieve the wellness goals, and gives corresponding coaching recommendations and suggestions in real-time through a personalized human-machine interface (HMI).

Interaction Requirements

The interaction between the eCoach and the coached person pursues three main goals: accessibility of the interaction, personalization of the communication modality, and adaptation of the system to the coached person's needs. For the accessibility of the interaction, different options addressing the HCI are already available in the literature, such as haptic interaction in virtual environments [31] or everyday interactions [20], voice-command [27], speech for low-literacy users [32], context-aware augmented reality [13] and adaptive text for disabled users [12].

Several options will be available for the personalization of the communication modality. The goal is to offer a range of possibilities to adapt the communication to individual's condition and context of the interaction. These include but may not be limited to: text, voice, sonified touch, olfactory or projected. In addition, the adaptation will take into consideration educational level regarding general knowledge and technology use, such as literacy and eLiteracy. Finally, the observations and recommendations will be carried out seamlessly, with minimal and customizable human intervention. This means that the coached person will select the degree of automatization of the decisions made by the eCoach, ranging from human-in-the-loop [17] to totally automated [9].

Technology Requirements

The proposed process of continuous wellness management, inspired by reinforcement learning [16], is illustrated in Figure 2.

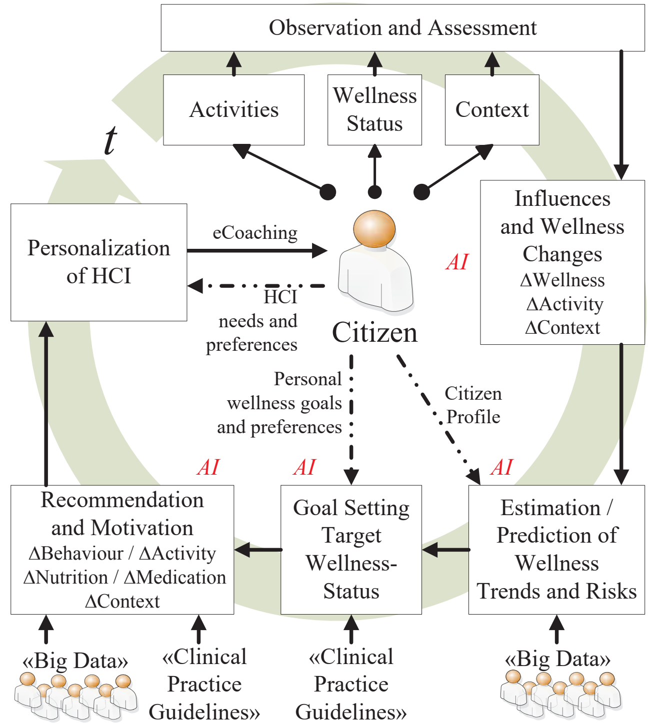

Figure 2: Continuous Process of Wellness Management

Citizens' User Profile:

The citizens' user profile is the basis to relate their individual observations to clinical practice guidelines and knowledge obtained from reference groups of "similar citizens", to consider individual wellness goals and preferences, and to personalize the HCI to individual usability needs and preferences.

The profile contains various characteristics, e.g. age, gender, geographical context (nationality, region, location, etc.), social context (e.g., married, family, etc.), general wellness status (e.g., known disease and health risks, blind/deaf, high blood pressure, allergies). Correspondingly, citizens are classified according to various parameters of affiliation, such as social affiliation, geographical affiliation, etc.

Observation & Assessment

The starting point for the development of a system for the automatic determination of optimal interventions to improve any individual's **wellness** from a holistic viewpoint requires a *model* for the description and evaluation of wellness, performed activities and interventions, and citizen's context.

The proposed observation and quantification covers the wellness assessment following Hoyman's wellness model [15], performed activities and interventions, and context parameters (Table 1). The measurement and quantification of the wellness status includes functional and physiological parameters, cognitive and mental parameters, social wellbeing parameters, and spiritual faith. The list of parameters in Table 1 is not exhaustive. Measurements of objective parameters are conducted for example with imperceptible wearable or implanted sensors, while subjective symptoms can be collected with standardized or widely adopted assessment tools.

	Observations and Assessments
Functional / Physiological Parameters	Health-related Wellness Medical Data: Pulse, Blood Pressure, Blood Oxygen Saturation, Blood Glucose, Weight, Heart Activity, etc. Musculoskeletal Parameters Activities of Daily Living
Cognitive / Mental Parameters	Speed of Processing and Response Time Working Memory; Task Shifting; Planning Mood Assessment and Determination Relation to Activities, Context, etc. (Music, Movie, …)
Social Well-being	Social Support and Integration Social Networks and Communication Activity
Spiritual Faith	Spiritual Perspectives (Sense of Purpose, Meaning of Life, Awareness of Inner Peace, Harmony, Hopefulness, Compassion for Others
Context Parameters	Time, Location Geographic Context (country, region, climate, weather, a.o.) Environmental Context (air quality, dust, smog, humidity, a.o.) Social Context (age, family status, …)
Activities Performed	Physical Activities Nutrition, Food & Drinking Medication taken

Table 1: Holistic Observation

In order to be able to understand and influence the impact of the multidimensional activities of the individual citizens on their wellness, our proposed eCoach concept also includes the measurement and quantification of holistic **activities**. The holistic perspective on activities includes (among others) physical activities, nutrition, and medication. This also allows distinguishing between the actually performed and the recommended activities and interventions, in order to consider the differences and respond, for example, to known phenomena as wrong medication. There is a potential overlap of the monitoring of activities with the assessment of functional and physiological parameters of the wellness status, such as the ones associated to activities of daily living (ADLs).

Besides fundamental **context** parameters as the time when and the location where a citizen carried out a wellness observation, further parameters as the geographical and the environmental context have an immediate or a long-term impact on the wellness status. In order to follow changes of the wellness status and influences over time, the observation should be continuously performed. This means carrying out periodic assessments or measurements on daily or more frequent level, or continuing measurements of periods of time.

Influences and Wellness Changes

Based on continuous observation, the eCoach determines the changes of the wellness status (ΔHealth) of citizens. It correlates these changes with those particular activities that are different from the normal activities (ΔActivity), and with any changes of context parameters (ΔContext). This leads to knowledge about the influence of activities, interventions, and context changes on the wellness status of citizen.

The observation of many citizens leads to reference knowledge about the statistical dependencies between changes of observed activities, context parameters, and changes of wellness parameters (see Figure 1).

Estimation / Prediction of Wellness Trends and Risks

Based on the continuous observations of individual citizens' wellness status over a certain period of time, potential wellness trends in terms of risks and improvements and their likelihood in a certain future period of time are determined. The historic knowledge about dependencies between wellness changes and influences (see above) of an individual citizen and reference knowledge from other citizens with a similar profile are used as input for applicable AI-technologies.

Goal Setting of Target Wellness-Status

The eCoach calculates a target wellness status for one (or different) defined point(s) in time in the future in terms of specific goals for selected wellness parameters. The determination of the target parameters and the goal setting considers the calculated wellness trend (see above) and the most critical wellness parameter(s), relevant clinical practice guidelines (CPGs), and personal wellness goals and preferences of a citizen.

Personalized Recommendations and Motivation

Personalized recommendations address the question "How can the individual wellness be improved from an observed holistic wellness-state A to a target wellness-state B with specific activities, interventions and context changes?". The determination of recommendations utilizes medical evidence (clinical practice guidelines), and individual and reference knowledge about the impact of activities and changes of context parameters on certain wellness parameters. Similar to the estimation and prediction of trends and risks, the eCoach finds those activities and context changes that are expected to have the best influence to achieve the defined target wellness parameter(s) (see above). The recommendations follow (analogue to the observations) a holistic approach, and include behavioral aspects (as physical activities, smoking, etc.), nutrition (change of type and amount of food), medication (in terms of type and dosages), and changes of context parameters (as change of room temperature, improvement of the air quality, avoiding smog, etc.). Personalized recommendations can be either “direct” activities, interventions and context changes, or “indirect” suggestions for actions and activities, that motivate a citizen for desired behavior changes. These recommendations are forwarded to the personalized HCI dialog, and the process continues with the reinforcement of the coaching by the observation and assessment of the actually performed activities and their effects on the wellness status.

Validation of the eCoach in the Field

The proposed eCoach concept will not be realized as a single application or service, but as a system of integrated components, spanning from end-user devices and applications for the interaction with the coached citizens, to infrastructure components for data communication, aggregation, and evaluation for knowledge generation and determination of recommendations. Correspondingly, the technological verification has to incorporate each system component and the overall integrated system. From a HCI-perspective, the achievement of the overall goal of the eCoach has to be verified. This includes (beyond others) studies of the impacts of the eCoach on the wellness and subjective quality-of-life of the coached persons, acceptance and usability aspects of the eCoach, efficiency gains of healthcare providers, and benefits for the health system and the society.

DISCUSSION

Case Study with Wearables

A digital health study [23] had exemplary demonstrated the potential of wearables to provide actionable health information. Wearables were used by healthy citizens for continuous observations of basic life signs, and basic learning techniques allowed learning the set of “standard” values for each individual participant. Utilizing the continuous measurements, algorithms could detect abnormalities, and recommended a medical examination even before participants had notable illness symptoms.

The proposed eCoach concept has a number of potential advantages:

- The eCoach can predict trends and the risk potential for further development of certain wellness parameters by utilizing individual and reference knowledge from continuous observation over longer periods of time to support diagnosis.
- Based on the estimated likelihood for a certain diagnosis, the eCoach can combine reference knowledge (based on clinical evidence) with knowledge aggregated from other citizens with a similar profile to determine what activity or change of context is recommended (in terms of the highest likelihood for a positive influence on the health status).
- Individual preferences for wellness and quality-of-life goals, such as a target fitness status, may be considered for individual recommendations.
- Utilizing continuous long-term observation of an individual citizen, the eCoach learns what multidimensional activities and context changes have positive (and negative) influences on the wellness of this person and, through it, adapt individual recommendations.

Case Study for Monitoring of COPD Patients

Current telehealth solutions for chronic obstructive pulmonary disease (COPD) patients (exemplary we look at a recent test system developed for a field trial in South-Norway in the EU-FP7 project United4Health [36]) can monitor daily glucose and SpO_2 levels, pulse, and other related symptoms to monitor patients’ health at home, and send alerts to nurses at a telehealth center when the data indicates alert conditions based on existing and generalized knowledge. However, the system is not linked to an exercise eCoach that is aware of patients’ condition, especially not of any lifestyle preferences as outdoor activities, etc. Any slight change of context parameters as the condition in the air and environmental quality may have a profound impact on a patient’s COPD condition. Using the proposed eCoach, the patient’s physiological parameters (e.g. heart rate, SpO_2 level, galvanic skin response, breathing rate) can be monitored in real-time while she/he exercises, making sure that any positive and negative changes are recorded. Based on the location-enhanced data from aggregated or community-based samples, the eCoach will be able to predict and pre-warn whether a patient should exercise at a particular time in a particular place. Using historical symptoms-related physiological data from a patient, the eCoach may improve the accuracy of the prediction and tailor the warning and recommendations accordingly. Moreover, as the data is triangulated with clinical data, observations, and recommendations, the eCoach can further improve the quality of the recommendations, based on expert’s feedback and diagnosis. Other lifestyle behavior including smoking, alcohol consumption and dietary intake can be monitored as part of the multidimensional activities profile of a patient. This ensures that exercise is not seen as the only (isolated) cause of symptoms, as they would have indirect/direct and short and long term impacts before, during or after the exercise. Location awareness and tracking of the patient’s changes of environment should also include the monitoring of indoor and outdoor conditions (e.g., temperature and humidity) and air pollution’s sources (e.g., pollens and dust) to create a more localized view of the context parameters.

The eCoach observation data over time will be aggregated for an individual and across all patients to improve the machine learning accuracy and to reinforce personalized recommendations. This allows avoiding two significant limitations of the decision support approaches of current telehealth systems for remote patient monitoring:

- The evaluation algorithms for monitoring data typically consider one-time data, i.e. only the latest reported observation data. Changes of certain wellness parameters over time and hence trends of the overall wellness status are not calculated.
- The decision support algorithms for the detection of serious or critical health conditions are often based on static rules and generic thresholds/cut-off values, with limited personalization according to individual health characteristics. This can lead to reduced accuracy and reliability of the triggered alerts.

User Scenario Revisited: Wellness Management Advantages with an eCoach

The eCoach has the potential to meaningfully involve citizens in their management of wellness and disease, with positive impacts on their perceived quality-of-life. We revisit the user scenario of an older patient previously described, but this time with the inclusion of the eCoach proposed in this paper.

Health Management supported by an eCoach

Interaction with Technology: AK will be explained when necessary and in an understandable and accessible way how to daily check her glucose and SpO_2 levels, pulse, and other related measures to monitor her health, with a comprehensible explanation of the results and the impact in her health.

Interaction with National Health System: AK's visits to her general practitioner will be on demand of the health professionals who are alerted by anomalies or risks in her daily health condition reports. Many of the visits will be virtually made, with the possibility to travel to specialized care facilities only when justified. In addition, new evidence-based practice coming from similar patient groups or disease conditions will be applied when suitable.

Traditional Statuses Assessment: AK's health status will be continuously assessed by the eCoach, alerting, warning or communicating any finding or risks detected in AK's individual health status. The detection system will be based on individual health status compared with evidence and clinically available evolution of patient groups with similar condition/s. The cognitive and mental status will be continuously assessed by the eCoach, with the same type of assessment and alert system as for the physiological health status. The social condition will be also registered in the system and monitored based on preferences and clinical advice. Finally, the interaction of these four components will be a central part of the system, taking into account the correlation and causality between them (e.g., influence of cognitive and mental cognition on somatic diseases and vice versa).

Complementing existing solutions

Mining Minds intends to complement the role of specialists by intelligent monitoring and smart coaching mechanisms. Through an advanced rule authoring tool the specialists handle the creation and management of health and wellness knowledge, hosted in knowledge bases. The evaluation of the services supported by Mining Minds requires feedback from the users. A feedback analysis component utilizes sources as explicit feedback provided by the user and implicit feedback obtained from the user behavioral responses.

The proposed eCoach can complement the Mining Minds framework by utilizing the concept of reinforcement learning, i.e. the utilization of automatically derived knowledge about the impact of (multimodal) activity and context changes on the wellness status ("Influences and Wellness Changes" component in Figure 2). The eCoach utilizes this individual knowledge together with reference knowledge for the automatic determination of multimodal recommendations under consideration of personal preferences and wellness goals.

IBM Watson started targeting specialized healthcare fields, specifically cancer research, extending also to other areas. The focus is on utilization of AI for clinical research, i.e., the generation of knowledge from analyzing structured and unstructured clinical data. The proposed eCoach requires this type of reference knowledge, and complements the determination of recommendations for treatments and multimodal activities with personalized preferences and optimal impacts. These recommendations are at the same time reinforced from the continuous observation and exploration of individual wellness status, activities and context that are not categorized as stored clinical data. The cognitive capabilities of Watson may potentially complement the personalization of the interaction with the coached user and the specialists with natural language and talk.

CONCLUSIONS

The proposed eCoach concept outlines the future citizen-centric eHealth services that integrate wellness management. This integration involves the development and adoption of technologies and innovations for continuous observations and data aggregation with health-IoT technologies. These technologies would include AI techniques for knowledge generation targeting evidence- and observation-based wellness support.

The main aspects of the eCoach include the reinforcement of individual recommendations based on the continuous observation of performed activities, context changes, impacts on the wellness status, and the underlying holistic approach for observation and assessment. These potentially allow for advantages on the personalization of coaching recommendations determined by computers to the specific needs of an individual coached human. In particular, the eCoach can support telehealth and remote patient monitoring (RPM) services with evaluation of observation data and the automatic provision of personalized support recommendations. A significant advantage is the ability to cover routine monitoring and 24/7 service availability for patients and healthcare providers.

Medical and healthcare experts will have the fundamental role in the eCoach-enabled system for citizen-centered wellness management to support the development, training, validation, and continuous refinement of the eCoach system components. Routine monitoring, checkup and diagnostics can be done by an eCoach, and the healthcare professionals will be able to focus on cases where direct contact with the patients is needed.

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