Video Camera in the Ambient Assisted Living System. Health Versus Privacy

The Results of the Online Questionnaire for the Healthcare Stakeholders

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Abstract Significant growth of the ageing population segment brings the necessity of additional healthcare investment. Besides somatic disorders, part of the older patient group suffers from Mild Cognitive Impairment and dementia. According to the World Health Organization, currently 55 million people worldwide suffer from dementia only. The projection is 75 million in 2030 and 132 million by 2050 (WHO, 2021). Mild Cognitive Impairment is often the first stage of dementia. Most of the patients with MCI and dementia are home-based. Ambient Assisted Living can improve the wellbeing of patients and their relatives without considerably raising the price tag for healthcare. In the current work, the questionnaire was created for healthcare stakeholders in order to conceptualize potential AAL for MCI patients. In this paper, the role of a video observation in AAL is analyzed with help of non-parametric respondents' group comparison.

Keywords Ambient assisted living · Mild cognitive impairment · Smart home · Video camera · Privacy · Vital signs · ADL

1 Introduction

The smart home is a home-based system of systems, which consists of monitoring sensors, connected together as a net to the analytical and automated appliances, with local and distant control of indoors management and environment. The smart home concept encompasses several utilitarian dimensions: in-house automated systems with control and monitoring; communication; health monitoring; entertainment [33]. Smart homes can be integrated with a smart IoT environment and permanent ubiquitous health monitoring under the aegis of Artificial Intelligence [3]. The medical aspects of AAL are divided into the supervision and monitoring part and support part. There are numerous AAL healthcare support systems, which can be subdivided into

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several groups in accordance with the needs of patients, who have systemic impairments, or its narrow type, built for patients with a singular pathology. Comparative analysis tends to be more technical than medical [28]. For a similar reason, important medical parameters are often treated together with less important ones. From the healthcare point of view, home-based patients need to be monitored with a focus on the critical parameters. The most important parameters are vital signs, such as heart rate, blood pressure, breath rate, body temperature. The top causes of death include heart diseases, vascular damage, e.g. stroke, and respiratory diseases [59]. Most of the health conditions can be observed with help of different sensors, which give necessary information immediately. They help to control the condition of the person, health dynamic, follow up of the medication and treatment procedures, subject to biological compatibility [34]. In the case of Mild Cognitive Impairment, besides possible somatic dysfunctions, moderate memory, cognitive and psychiatric impairments create additional requirements for the AAL system [9].

2 Medical Data Registration in AAL

Vital signs and behavioural patterns can be registered with help of sensors. The data is collected via sensors' network and transmitted with help of middleware to the analytical tools. An alert is set on in the case of an emergency. The long-term problems can be followed up and general condition and level of representational independence evaluated.

2.1 Vital Signs

2.1.1 Heart Rate

Heart function is central to wellbeing. The resting heart rate of a healthy adult person is normally regular and has 60–80 beats per minute. It can vary with physical and emotional load, medication intake or underlying medical conditions. Heartbeat rate, regularity, volume, peripheral signs of blood perfusion give important information about the health status. Ischemic heart disease, arrhythmia, heart valve pathologies, vascular diseases are diagnosed and controlled with permanent checks of these characteristics. The heart rate can be measured by non-invasive Smart Wearable Sensing devices (SWS). Sensors or SWS are placed on the heart area, major arteries, peripheral arteries. They are pulse meters, electrocardiogram (ECG) sensors or SWSs, echo cardiac sensors. Blood perfusion in different body parts can be assessed by electroplethysmography and photoplethysmography techniques [35]. ECG, besides the heart rate and its rhythmicity, gives information about potential changes in the myocardial integrity and cardiac conduction condition. In some cases, sensors are seamlessly implemented as a part of smart shirts with textile-integrated non-invasive magnetic sensors [55]. They often are worn as wristbands or similar wearable items. There are ways to assess heart rate distantly, for example with the help of Doppler radar [32].

2.1.2 Breath Rate

Respiratory diseases are the next major factor of pathology and death. The breathing rate of a healthy adult person is normally relatively regular, with 16–20 cycles of inhalations and exhalations per minute. The BR can be measured by wearable on-body sensors, wearable seamless shirt-integrated sensors, wearable breath analysis sensors [29]. The last ones can measure exhaled CO_2 to evaluate breath effectiveness. Sensors can be used to control exhaled acetone to control glucose metabolism for patients with diabetes [41]. Blood oxygenation is often measured by peripheral photoplethysmography and can be combined with pulse rhythm measurement and tissue perfusion level monitoring. Exist different wearable types of sensors for permanent use, designed as earbuds, finger rings or wristwatches [53]. There are also methods of distant respiratory rate monitoring with help of infrared Doppler sensors by the Kinect [37].

2.1.3 Blood Pressure

The normal arterial blood pressure of a healthy adult person is 110–140 mmHg systolic and 70–90 mmHg diastolic. The BP directly reflects myocardial function, heart valves integrity and functionality, and indirectly neuro-humoral heart rate, vascular tonus and blood volume regulation. The blood pressure can be measured by wearable pressure sensors, placed on the skin above the underlying subcutaneous artery. Usual places are: wrists, biceps, ankles. The measurement can be done with help of an inflated cuff, cuff-less pressure sensors, cutaneous tension sensors, photoplethysmographic sensors, measurement of pulse wave transit time, by combining two sensors along with the blood flow [63]. Some researchers propose ultrasound sensors [61]. Invasive methods are used to measure blood pressure in the main blood vessels to control their integrity [25]. Sometimes other bodily liquids require pressure measurements.

2.1.4 Body Temperature

Surface Body Temperature (BT) of healthy adult person usually homeostatically fixed around 36.6 °C if measured on the skin or in the oral cavity. It is an important parameter of metabolism. Core body temperature is higher and achieves a level of 38 °C. Temperature is measured through the contact body wearable sensors or distantly, with help of infrared sensors. Wearables are designed in different forms as bracelets, watches, jewelry, smart clothes. Non-contact infrared sensors are used less often for body temperature measurement. However, systems based on the temperature detection proposed for the indirect cardiac rate measurement [19] or breath rate measurement [4].

2.1.5 Physical Activity

The normal gait as a physical process is divided into several phases, which repeat cyclically. The gait cycle usually is comprised of eight phases. It can be structured as two big sequential phases for the right and left leg, with stance taking 62% of the time and swing 38%. Each phase is then subdivided into four stages. One of the most important parameters is walking speed. In the metastudy, speed measurements are checked in 40 studies on more than 23,000 adults in different countries [10]. Normal walking speed is around 1.2–1.4 m/s, while pathological is supposed to be lower than 0.6 m/s [18]. Abnormal walking may reflect musculoskeletal pathology, neurological dysfunction, skin pathology or more general abnormality. Some researchers propose walking speed to be the sixth vital sign (the fifth is Body Mass Index, BMI). There are numerous ways to measure convenience in-home walking speed. Stationary sensors are based on a Doppler effect or electromagnetic tracking system, wide area pressure sensors, furniture pressure sensors, video and audio sensors. Wearable inertial sensors include accelerometers, gyroscopes, electromyographic sensors, pressure sensors, goniometers [54]. Accelerometers can be used to measure acceleration-deceleration and start/stop time, because they may change in some pathological conditions. More complex activities than walking are also routinely registered in most AAL systems. Utilities usage [17] or mounted sensors, signaling about refrigerator usage, doors and windows operation, other activities are usually monitored with help of different sensors and ontological models [6, 22]. Walking speed can be predicting sign for the future health condition [38], as well as Activities of Daily Living and Instrumental Activities of Daily Living (ADL and IADL) [43, 48]. ADL is estimated by the level of independence with: bathing, dressing, toileting, transferring, continence, feeding.

2.2 AAL for MCI and Dementia Patients

2.2.1 Diagnostic Aspects

Standard intelligence is generally reflected by IQ. The normal IQ is 85–115 (100 ± 15), ± 1 SD. MCI is diagnosed, when a permanent general IQ decline from a previously normal level is lower than 85 and higher than 70. Patients with dementia have stable IQ lower than 70. There are multiple methods of intelligence tests, various types of intelligence and diagnostic is non-trivial, but for simplicity IQ level is relevant enough, with more than 50% cases of MCI and dementia constituted by Alzheimer Disease (AD). There are many more causes for MCI and dementia: pseudobulbar affect, Parkinson's disease, frontotemporal lobar degeneration, Lewy body disease, vascular diseases, traumatic brain injury, substance/medication use, HIV infection, prion diseases, Huntington's disease [42]. Dementia as a condition has specific modes of behaviour. Patients have problems memorizing necessary information and have difficulties performing everyday tasks. Reminders have to be more persistent, patient and avoid provoking a negative emotional reaction. Unfinished tasks, like open doors, gas stoves, the water supply may have adverse results. Misuse of objects creates danger for patients, their close relatives, carers, neighbors and visitors. Wandering without a clear objective, especially in an environment with obstacles, stairs, windows without protection is potentially harmful to dementia patients.

2.2.2 ADL

While MCI can be transitory between normal cognition and dementia, this pathology may stay for years and condition, in some cases, can improve. MCI is not easily diagnosed. ADL of patients with MCI is found to be lower than that of healthy old people. It can be connected to general activity during the day and to walking speed as well [20]. Comparative analysis of data sets also shows the difference in IADL. It can help to detect cognitive decline early [40]. Special service-oriented application (SOA) AAL platform "DemaWare" is created to address part of these issues, but partially based on obtrusive camera wearing for complex activity recognition [51].

In the European AD automated diagnostic project, Dem@Care patients' movement data is collected from the wearable ankle-mounted accelerometer. Additional data adaptation by creating more day and week time domains improves automated diagnostic [8]. Memory is one of the functions, which often suffers profoundly in dementia and MCI. It creates multiple problems, especially with repetitive tasks. Some AAL components are built to compensate for the loss of the function. There are attempts to create systems (HERMES) with the ability to remind about daily tasks, free time use [14]. The addition of smart objects, smart pillboxes, electronic calendars, smart white goods with reminders creates a better environment for patients with memory loss.

2.2.3 Spatial Movement

The connection between ADL tasks and cognitive impairment is well known and often reported [36]. Moreover, a strong positive correlation between quantitative gait characteristics and dementia is found in several studies. Mostly affected are step velocity and step length. A number of daily bounds (sessions, rounds) negatively correlates with cognitive status [27]. In some studies proposed prediction of the mental status change, based on the walking features, as speed, angular velocity and balance [30]. Other researchers found only a spatial correlation between gait and cognition for healthy old people [56]. However, in a major longitudinal study of 2938 mentally healthy participants, of which 2233 participants were reassessed and 226 developed dementia. Future decline correlated with walking speed. It is also proposed that diminished mental processing speed plays a crucial role in lower walking speed. One standard deviation in walking speed shows a potential increase in the possibility of future dementia [60].

2.2.4 Sleep Abnormalities in MCI

While sleep deficit or disturbed rest often have negative impact on mental abilities, there are signs of the influence of cognitive dysfunction or conditions, leading to it, on the rest/activity patterns and sleep architecture. Sleep and wake pattern is often disturbed in MCI patients [16]. Ability to register patient activities in AAL during day and night are clearly demonstrated [52]. These findings can be supported on the level of EEG registration. These pathological changes can be predictive in the case of MCI and correlate with deterioration. Specific signs during non-REM sleep phase show future MCI in aging patients [52].

2.2.5 Mental Health AAL Applications

Monitoring of mental health cases in the AAL system can be divided into two big groups. One deals with psychiatric emergencies, such as suicide, psychotic events, major depression, alcoholic or drug-induced events. In every such case, the patient is potentially dangerous for himself through self-harm or self-neglect or can be dangerous to other people. The other type is long-term supervision, which can deal with emergencies, but mainly intended to be diagnostic and supportive in the case of a chronic condition with potential for physical and mental deterioration. Behaviour detection is based on the complex events analysis, activity time ratio, daily activity rates, complex event processing (CEP) and pattern recognition against existing pre-collected sets [58]. Other systems are focused on the RFID of GPS objects usage [21]. For emergency cases, different prediction models are based on the sensors combinations and behavioural data sets [1]. Other systems propose a connection with previous patients' records for better diagnostics [2]. Identification and prediction of abnormal behaviour with the help of neural networks (NN) are proposed by another team [26].

2.3 Video Observation in AAL

There is a number of observation methods in the AAL. Video cameras are one of the frequently chosen types of sensors. While they are very useful for communication, operating cameras for monitoring in AAL is supposed to be invasive and raise concerns about patients' privacy. There are intermediate solutions when the image is reproduced as an abstract imitation. However, this method of representation is relevant to other positioning systems as well. In addition, video stream demands higher requirements for the data transfer and, subsequently, higher energy consumption. Several types of video observation are suggested. The usual RGB or RGB-D sensors are part of several AAL projects. Infrared and thermal cameras are another type. Optical sensors of different types are also utilized in AAL. All types are used for fall prediction and report, general well-being and medical observation, ADL measurement, communication and abuse prevention. The cameras can be static, movable, wearable, used as a group or in combination with other sensors [45].

As multysensor ubiquitous system can be costly and laborious to implement, video cameras represents reasonable price and effectiveness. The wearable camera, despite some specific advantages, e.g. demonstration the personal view and reflecting ADL and spatial activity, is restricted by lower compliance, certain level of user inconvenience and battery life limitations [12]. Privacy concerns are also high [5].

Laser-based optical systems can be utilized for positioning or fall-report. However, there are some difficulties to adopt security technologies for the AAL needs.

3 AAL Evaluation Methods

Existing and planned AAL systems have to be evaluated, validated and tested. Several methods are used for surveys and assessments. There are also theoretical methods, modeling in silico and practice, prototyping, live-in lab experiments and dry runs. After the start of the practical use data from the system and stakeholders is routinely collected and assessed with help of analytical tools.

3.1 Conceptual Stage

Health, WHO Quality of Life, WHOQOL survey and questionnaires are used for patients [39]. Healthcare specialists and caregivers formulate medical and social requirements and then the information is presented to technical specialists for conceptual validation, reference design and prototyping. The opinion of the social institutes and caretakers is also taken into account. At this stage, initial questionnaires are presented to stakeholders. The choice of every element in the system is based on the cross-section of requirements, from the skeleton to the user interface in later stages. Architecture is more influenced by technical standards.

3.2 Model

An initial phase demands the formulation of functional requirements, based on stakeholders needs. ADL, IADL with help of Prototype is envisaged with help of modeling, scenarios creation, personas and simulations. Data flow evaluation and model quality control are used, with analysis of acquisition, transmission and usage [23]. In the first stage, sensors are chosen and calibrated. In the second stage ways and periodicity of transmission are analyzed, as well as security. In the third stage storage, backup and potential recovery are envisaged. Personas are used and portraits of potential users are generated. Father, more narrowly focused questionnaires can be utilized together with expert reviews.

3.3 Prototype

In the next stage, the prototype is tested for usability, functionality and interoperability by special tools or in living labs [13]. Experiments and questionnaires are instruments on this stage, as well as reviews [44]. While technical and instrumental measures are more objective and based on external metrics, questionnaires tend to be more subjective instruments and require different instruments of analysis. Both approaches have to be balanced in every case. For example, in living labs, there are different approaches to the information presented for the actors or patients. Some can be informed about testing, and others are instructed afterwards. In every case, the nature of questionnaires and surveys may differ.

3.4 Impact Assessment

Wider impact assessments include social, financial, industrial and political impacts, as demonstrated in the "Learnings from the 2019 and 2020 AAL Impact Assessment Final report." by http://www.aal-europe.eu and Technopolis group. There are three main types of frameworks of impact evaluation: Re-EIM, MAST and UTAUT. [31]. Re-EIM is an acronym of "Reach", "Effectiveness", "Adoption", "Implementation". Reach speaks about the type and size of focus groups, inclusion and exclusion criteria. Effectiveness measures all effects, including positive and negative impacts. Adoption calculates the number of stakeholders, who adopted the scheme or system. Implementation registers social, financial, administrative and other costs. Maintenance is a measure of long-term adoption, level of institutionalization or routine practice change. MAST is a Model for Assessment of Telemedicine. It is a multidomain approach to healthcare IT systems, which include Ambient Assisted Living. It is divided into three stages: a preliminary assessment, multidisciplinary assessment and transferability assessment. At every stage multifaceted analysis of social, administrative, financial, ethical and other aspects is done. Safety, effectiveness, maturity, possibility to be practically adapted are surveyed. The UTAUT stays for the Unified Theory of Acceptance and Use of Technology. It is a model framework, which consists of four elements: performance expectancy, effort 31 expectancy, social influence and facilitating factors [57]. There are also price value, hedonic motivation and habits in the extended model. The behavioural intention in the model is also influenced by age, gender and experience. All factors lead to user behaviour. Every model can be used separately, partially or in full, with extensions, in combination with other models or provide elements fora specially constructed framework.

3.5 Questionnaires

One of the widely employed methods is a questionnaire. Economical and policy institutions create a significant impact on the AAL provisions. At the same time stakeholders: technical service providers, medical service providers, e.g. institutions and workers, end-users, such as patients and family carers, are the most important immediate players in the field of AAL. Current, prospective and retrospective assessment of stakeholder opinion through the survey is an important tool, addressing various aspects of the AAL. The level of acceptance, satisfaction, informed opinion or professional view is significant in the design and exploitation of AAL systems. Questionnaires can be subjective report tools but include objective information e.g. technical or biomedical parametric qualitative and quantitative data for comparison [7]. Objective information can be obtained by other means than questionnaire. Psycho-social factors, such as subjective acceptance, readiness to learn new technologies or to be involved in services with extensive AAL components are also important. Results can be presented as qualitative data, but scaled questions and frequency tables allow formal non-parametric statistical analysis.

3.5.1 Questionnaire Framework

The general framework depends on the questionnaire objectives and weights, attributed to certain metrics and variables. It is planned on the stages of conceptualization and questionnaire design [11]. Extensive literature review leads to the general understanding of the necessity, goals and the type of respondents the survey is targeting. While the concept influences every part of the questionnaire and every change in it, the nature of the expected category of interviewees is quite clearly split between the general population sample and the expert group. It affects the length of the survey and cognitive load, required from the respondents. The design depends on questionnaire structure, complexity, types of questions, wording, instructions, types of feedback and ways of administration. When the questionnaire is completed, it is tested, reevaluated, adjusted and implemented for data collection.

3.5.2 Types of Questionnaires

There are several types of questionnaires [46]. They depend on the research goal, focus group, type of questions, length and depth. Questions can be more qualitative or quantitative, open and closed, dichotomous, with simple dual answer options, or multiple options, factual or opinion-based. Scaled questions of several Likert types are also often used to measure level or degree. Complex questions can be designed with internal subquestions and mixed options. Butteries of questions and specific batches can be arranged in sections or be spread randomly. Questionnaires are used in a direct interview, by mail, phone, online application, mobile app. The obtained information is often analyzed with the help of statistical instruments. The separate complex research class is formed by multifaceted surveys, designed with axes for several stakeholders. AAL4ALL project [15], run as an interdisciplinary, academic and industrial scheme. This project, for example, is created with a goal to answer questions about applicability, affordability and necessity to provide AAL as part of the communal healthcare program. It includes three major groups of respondents: patients as end-users, informal caregivers and healthcare and social care providers. Another complex approach is to present the same type of questions to different stakeholders in iterations, known as Delphi Survey, named after a well-known historical oracle. Questions are iteratively updated by answers and re-presented to the "oracle" panel of experts [49]. Results are scaled, which helps to rank importance inside of the questions' groups.

3.6 Questionnaire. Statistical Analysis

3.6.1 Reliability

Several well-established tests are applied for examination of internal consistency and reliability of the questionnaires. Split-half methods of different complexity are usually employed. Tabled results of the Likert scale responses undergone specific procedures. Cronbach's Alpha (tau equivalent), Revelle's beta, McDonald's omega, Guttman's lambda are described below. Test-retest reliability is checked by Cohen's kappa [47].

Cronbach's Alpha

Tau-equivalent or Cronbach's alpha is a measure of covariance between elements of the questions group. This parameter counts "dimensions" of the questionnaire and their interrelation with the help of the covariance matrix. Every respondent result is compared with the entire count of each observation. The higher number of "dimensions" and a stronger correlation between them gives higher results for alpha. Cronbach's alpha results are considered valid in the range of 0.8–0.9, with variations up and down. Alpha below 0.5–0.65 is considered to be a sign of low reliability, while higher than 0.9 shows redundancy or a high number of "dimensions".

$$\alpha = \frac{N\overline{c}}{\overline{v} + (N-1)\overline{c}},$$

where N is set power, $\overline{c}$ is average covariance for every element, $\overline{v}$ is average variance. Kuder–Richardson Formula 20 (KR-20) $\frac{n}{(n-1)} \times \left(1 - \frac{(\Sigma x \times y)}{v}\right)$ is a variant of alpha for binary items in dichotomous questions, where n is a size of the sample, v is variability, x is the proportion of respondents answering positively, y—the proportion of respondents, answering negatively. KR-21 is used for questions with a close rate for questions, where m is mean count for the test:

$$\frac{n}{(n-1)} \times \left(1 - \frac{m \times (n-m)}{(n \times v)}\right).$$

Revelle's B

Beta is minimum or lowest split-half type test estimate of internal reliability.

$$\beta_{x_1} = \frac{c_{dp_1} - c_{dp_2} \times c_{p_1,p_2}}{1 - c^2_{p_1,p_2}},$$

where c is correlation/covariance, p_1 and p_2 are predictors and d is dependable variable. Beta is supposed to be more conservative estimator, than alpha—the later has tendency to "overshoot".

McDonald's Omega

Omega as a parameter is similar to alpha. Confirmatory Factor Analysis (CFA) of factor F for n variables X_n are connected by load l_n and influenced my the error e_n.

$$\omega = \frac{\left(\sum l_n\right)^2}{\left(\sum l_n\right)^2 + \left(\sum \sigma_{e_n}\right)^2}$$

The additional level of factor analysis is added. The covariance matrix of results is obliquely rotated and then so-called Schmid-Leiman or S-L second transform is performed.

$$C_m \approx \sum\left(FSS^T + D_m^2\right)$$

where C_m is square $p \times p$ correlation matrix, F is factors matrix $n \times n$, S is $n \times p$ matrix, D_m^2 is $n \times n$ diagonal matrix. F is transformed to create F_m second-order correlation matrix.

McDonald's omega is supposed to be a more reliable coefficient than Cronbach's alpha. Levels of 0.7–0.95 show reliability of the results.

Guttman's λ2

Coefficient lambda is similar to alpha and tau-equivalent of reliability. It comes in several grades, starting from lambda 1. The difference is that for alpha is used more random algorithm, while lambda has a lower level of randomness. Covariance between sums of items and average variances are included into the formula:

$$\lambda_2 = \left(1 - \frac{\sum C_i}{C_x}\right) + \sqrt{\left(\frac{n \times \sum \sum C_i^2, _j}{C_x^2}\right)},$$

where $C_i^2, _j$ is covariance between results.

Lambda can be employed for more complex tasks. Lambda is usually higher than Cronbach's alpha. Values for reliable test are 0.8–0.95.

3.6.2 Correlation. Non-parametric Methods

There is a significant difference between parametric and non-parametric analysis. Usual statistical analysis is based on mean, variance, standard deviation, analysis of probability distribution and ANOVA, analysis of variance. Parametric methods often consider continuous data. Non-parametric data does not have a usual tendency for normal distribution and often discrete ranks. Nominal data is presented by nominal categories, while ordered data is also scaled. In non-parametric methods, most important measurements are mode, median, quartiles and interquartile range (IQR) [50]. Sets of data can be compared between each other to trace independent or common sources of results [24].

Mann-Whitney-Wilcoxon Test

Mann-Whitney-Wilcoxon Test checks the equality of two ordinal sets of data. Sets can be of unequal size. MWW test calculates "unbiased" U parameter. It checks the equality of distribution and the supposed independence of sets.

$$U = N_x N_y + N_x \frac{(N_x + 1)}{2} - \sum R_x$$

where N_x is set X, N_y is set Y and R is the sum of ranks. Precision of the test is lower with significant difference between sets there is a possibility for type II error in this case.

Kruskal–Wallis Test

K-W test or one-way rank analysis of variance (ANOVA), calculates H parameter to test mutual dependency of data sets. KW test is designed for two or more sets. The size of data sets can be unequal, because the calculation does not involve paired comparison.

$$H = \frac{12}{n(n+1)} \sum_{x=1}^{m} \frac{R_x^2}{n_x} - 3(n+1)$$

where n is certain data set power, m is number of groups, R_x is rank of x and x is number of the data set.

Two or more samples are compared. Big differences between sets can cause type I error, giving false positive results.

Spearman's Rho

Spearman's Rho correlation coefficient is a rank analogue of Pearson coefficient. When Pearson coefficient is applied for continuous data, Spearman's Rho can be used for non-parametric ordinal data. Two sets of the same size, for example answers on two questions, are compared pairwise.

$$\rho = 1 - \frac{6 \times \sum \left(R_x - R_y\right)^2}{n\left(n^2 + 1\right)}$$

where n is number of results.

4 Research

4.1 Method

Medical and social requirements for the AAL are formulated on the conceptual stage. There are several ways to find answers, theoretical and practical. Any route gives only partial vision. The needs of caretakers and healthcare stakeholders are collected by questionnaires and expert suggestions. The process can be iterative, mixed and include detailed recommendations. The best approach is to try to encompass all these raised problems in one research to weight and compare information between subquestions. In the conditions of limited research complex questionnaire for healthcare stakeholders is the easiest way to obtain necessary preliminary answers. Web-based questionnaire is easy to deliver worldwide. In current research Google Forms-based questionnaire was used.

4.2 Reliability

Questionnaire was tested on several runs before wide implementation. Reliability of the questionnaire is checked in Jasp 0.14.0.0—for scaled questions. Responses on 50 questions have McDonald's = 0.899, Cronbach's = 0.911, Guttman's 2 = 0.921. ω α λ The highest values in the questionnaire are: for Cronbach's is 0.920; for McDonald's is α ω 0.934; for Guttman's 2 is 0.932 (Table). Values above 0.9 may reflect (a) redundancy of the λ test—there are specially added questions in some dimensions to recheck values of the responses (b) multidimensionality of the test. 15 questions with opposite scales and negative results in the table were excluded from analysis. In this section is presented simple analysis and comparative description analysis between 76 sections and questions without group results comparison. In some cases Spearman's Rho pairwise correlation test is performed.

4.3 Focus Group

The Ambient Assisted Living system design has to be based on the opinion of the main stakeholders: healthcare professionals, technical stakeholders, administrative stakeholders and patients. Every opinion group is important, and the opinion has to be assessed appropriately.

Healthcare professionals represent a specific cross-section of society with a skilled understanding of patient's needs in specific conditions. Years of focused training and practice give a wealth of information about the needs and problems of home-based patients. Still, there is a range of possible opinions, dictated by the professional view, personal experience and wide scope of technical, social and organizational knowledge.

This study is based on a complex questionnaire. The questionnaire is presented to the healthcare workers, mainly medical doctors. In order to achieve the best possible combination, heterogeneous groups of medical professionals from different countries are included. In order to obtain as much and as wide information as possible and to keep the sample big enough despite complexity of the questionnaire all specialists with finished medical education or clinical psychology diploma were considered.

The respondents were reached via web of personal contacts and with help of social media. The main reason was to eliminate subjective element of self-report about profession and professional experience.

More than three hundred medical specialists were contacted in the USA, Canada, UK, Netherlands, Germany, Switzerland, Sweden, Greece, Israel, Armenia, Ukraine, Belarus and Russian Federation and asked to answer the questionnaire. Around 120

Table 1 Age and gender structure

	Number	Minimal-maximal	Mean, years	Median	Mode
Age	60	21–63	49.9	50	50
Gender: F	29	21–60	49.0	50	50
Gender: M	31	42–63	50.7	50	49

agreed to participate, of whom 60 answered all questions. Those who did not finish the questionnaire named several reasons for it: unknown topic, the length and complex nature of the questionnaire, heavy workload and shortage of time because of the COVID-19 pandemic. Country name was removed from the questionnaire for reason of required anonymity. However, there was no informally registered difference in the approach of specialists, depending on the country of practice or residence. Age and gender were collected for statistical necessities.

4.3.1 Age and Gender Structure

Age and gender were collected for statistical necessities. The age is from 21 to 63, with average age 49.9 years (Table 1).

4.3.2 Medical Profession

There are 60 respondents. Of those who answered, there are 41 medical doctors, 10 nurses, 4 paramedics, 2 dental medicine doctors, 3 clinical psychologists. Some information is available about medical doctors' specialization. Limitations arose from wide options of the question about the medical profession, so some doctors did not mention their specialization. The additional matter is a possibility to have more than one profession and report only one, often the most recent. Physician, MD—14. Psychiatrist, narcologist—9. Neurologist—3. Geriatric consultant—2. ONT consultant—1. Gynaecologist—2. Surgeon—1. Family doctor—1. Anaesthesiologist—4. Haematologist—1. Paediatrician—1. Dentist, DMD—2. Urologist—1. Traumatologist, Orthopaedist—1. There was no option to learn nurses' specializations. The age distribution by major professional groups is presented in Table 2.

4.4 Health Versus Privacy. Results

Data is obtained from answers to multiple-choice questions, matrix questions and scaled item-by-item questions. Healthcare and IT experience is projected on questions about medical aspects of technology implementation. Results are assessed with the help of descriptive and analytical statistics. Google Forms provide not only an

Table 2 Age distribution for professional groups

	Age				
	DMD	MD	Psychologist	Nurse	Paramedic
Valid	2	41	3	10	4
Missing	0	0	0	0	0
Mean	49.500	50.951	48.667	45.900	50.250
Median	49.500	50.000	52.000	49.500	50.500
Mode [a]	48.000	49.000	40.000	50.000	47.000
Variance	4.500	37.298	57.333	100.100	6.250
Range	3.000	32.000	14.000	35.000	6.000
Minimum	48.000	31.000	40.000	21.000	47.000
Maximum	51.000	63.000	54.000	56.000	53.000

[a] More than one mode exists, only the first is reported

easy way for questionnaire implementation but also a preliminary analytical structure. Numerical data and percentages are presented for scales and frequency tables, graphs and histograms provide visual information. All data can be extracted as an XML file. Excel and analytical software help to analyze data. JASP package is used for data analysis.

I this chapter are provided only descriptive statistics for statements about video camera in AAL. All group comparative analysis is not shown.

4.4.1 Descriptive Statistics

Sensors in AAL, Answers' Frequency Table

Table 3 with more than one possible answer per question per option.

Discussion: There is a tendency is recognition of the prominent role of video cameras in the AAL system—for security (68%) and for abuse prevention (75%). At the same time the invasive nature of video registration is acknowledged. 48% of the respondents think that video sensors can be switched on only at the time of the emergency. Still, wearable sensors are perceived as more invasive (47%) than video cameras (33%). 72% of the interviewees marked video camera as second best for communication. Microphone received 82% for the communicative purposes. Microphones are recognised as second best for the security and abuse prevention.

72% of the respondents believe that video camera is best sensor in the AAL system for the MCI patients. 68% support the importance of the microphones in the system. Preference of the video camera as one of the most important sensors, even if it can be switched on 24 h 7 days a week, raises question about privacy of the patient.

Table 3 Sensors in AAL, answers' frequency table

	Video camera	Microphone	Infrared positioning sensor	Mechanical pressure sensors	Wearable sensors	Temperature, air sensors
Most important sensors in AAL	38 63.3%	35 58.3%	38 63.3%	33 55.0%	49 81.7%	14 23.3%
The best combination of sensors in AAL	38 63.3%	34 56.7%	41 68.3%	35 58.3%	48 80.0%	18 30.0%
These sensors are not necessary for AAL	18 30.0%	14 23.3%	8 13.3%	10 16.7%	4 6.7%	35 58.3%
These sensors are too invasive to be switched on 24 h a day/7 days a week	20 33.3%	14 23.3%	12 20.0%	11 18.3%	28 46.7%	6 10.0%
These sensors can be switched on only in emergency	29 48.3%	21 35.0%	15 25.0%	14 23.3%	10 16.7%	21 35.0%
These sensors can be used for communication	43 71.7%	49 81.7%	6 10.0%	4 6.7%	7 11.7%	3 5.0%
These sensors are most informative	27 45.0%	21 35.0%	28 46.7%	28 46.7%	44 73.3%	10 16.7%
These sensors are least informative	8 13.3%	16 26.7%	13 21.7%	12 20.0%	8 13.3%	33 55.0%
These sensors are important for security	41 68.3%	29 48.3%	23 38.3%	11 18.3%	19 31.7%	11 18.3%
These sensors can help to prevent abuse	45 75.0%	30 50.0%	14 23.3%	9 15.0%	17 28.3%	7 11.7%

Sensors in the Ambient Assisted Living System for Patients with Mild Cognitive Impairment. Statements and Results

A. "The video camera is the best sensor in the AAL system for patients with Mild Cognitive Impairment".
B. "Microphones are very important in the AAL system for patients with Mild Cognitive Impairment".

Table 4 Descriptive statistics by statements, "Sensors in AAL"

Statement	Likert 6–10 (%)	Likert 8–10 (%)	Likert 10 (%)	Mean	Median	Mode	Quartiles	IQR
A	43; 71.7	26; 43.3	9; 15.0	6.6	7	7	5; 7; 9	4
B	41; 68.3	27; 45.0	8; 13.3	6.6	7	8	5; 7; 8	3
C	39; 65.0	26; 43.3	11; 18.3	6.5	7	10	4; 5; 7	4.5
D	38; 63.3	25; 41.7	11; 18.3	6	7	10	3; 7; 9	6
E	35; 58.3	23; 38.3	6; 10.0	6	6	1	3.5; 6; 8.5	5

C. "The video camera and microphones are too invasive to be used 24 hours a day/7 days a week as AAL sensors for patients with Mild Cognitive Impairment".
D. "Video cameras and microphones can be used in AAL only for emergency".
E. "Video camera and microphone can be used in AAL for patients with Mild Cognitive Impairment for communication only" (Table 4).

Discussion: Vitally important sensors have to be part of AAL for MCI patients according to most of the opinions. This includes wearable sensors, door and windows' sensors, smart water and gas leak sensors (These statements are not shown here). However, there is less consensus about invasive ones', such as video camera and microphone, or sensors, controlling positioning and gestures, and smart electricity sensors. While nearly two thirds of respondents generally support use of all these sensors, there is a disagreement. Support for video camera and microphone use is quite significant. There is a vision of necessity to use it not only for communication, even though it might be switched on 24/7.

Privacy of the Patient with Mild Cognitive Impairment in a Home Equipped with the Ambient Assisted Living System. Statements and Results

A. "Patient's health is more important than privacy issues in AAL".
B. "Privacy is more important than the patient's health in AAL".
C. "Privacy issues in AAL can harm the mental health of patients with Mild Cognitive Impairment".
D. "Patients with paranoid thoughts are not advised to live in a home with the AAL system".
E. "Emotionally sensitive patients are not advised to live in a home with the AAL system".
F. "AAL system is not more invasive than traditional healthcare" (Table 5).

Discussion: There is a tendency to put health problems before privacy problems, even though a significant part of respondents disagree with this less balanced, by their opinion, view. There is also no consensus about the danger of AAL systems for emotionally sensitive patients or those with paranoid thoughts. At the same time more than half of respondents see AAL system more invasive, than traditional healthcare

Table 5 Descriptive statistics by statements, privacy of patients with MCI in AAL

Statement	Likert 6–10 (%)	Likert 8–10 (%)	Likert 10 (%)	Mean	Median	Mode	Quartiles	IQR
A	41; 68.3	27; 45.0	15; 25.0	7	7	10	5; 7; 9.5	4.5
B	13; 21.7	7; 11.7	3; 5.0	4.1	3.5	3	2; 3.5; 5	3
C	35; 58.3	26; 43.3	14; 23.3	6.5	7	10	5; 7; 9	4
D	36; 60.0	18; 30.0	5; 8.3	6	6	8	5; 6; 8	3
E	32; 53.3	15; 25.0	3; 5.0	5.7	6	5	5; 6; 7.5	2.5
F	21; 35.0	9; 15.0	2; 3.3	4.8	5	5	3; 5; 7	4
G	36; 60.0	20; 33.3	6; 10.0	6	6	8	4.5; 6; 8	3.5

system. There is correlation between answers to questions A and G. Spearman's Rho $r_s = 0.34036$. *P*-value is 0.00779. There is also correlation between answers to questions E and G. Spearman's Rho $r_s = -0.25529$. *P*-value is 0.049.

5 Conclusion

The decision about the necessity for inclusion of video sensors into the general AAL and AAL for MCI patients design depends at the same time on the healthcare needs and technical solutions and feasibility.

For medical reporting, communication, abuse control and security video cameras are supposed to be suitable by 72%—they believe it is the best sensor. Microphones are supported by 68%. Still, 65% of the respondents agree that video cameras and microphones are too invasive to be switched on 24/7, and 63% think they can be turned on in the case of an emergency. Only 58% agree with the statement that video cameras have to be used for communication only.

The solution to the privacy problem can be technological. The use of another type of sensors, ways of the information presented and switching on only in the case of emergency are practical ways to lower the intrusive nature of observation and to improve patient's privacy. Infrared motion registration is seen as important by 77% of the respondents. 72% think gesture recognition is necessary for the AAL system for MCI patients. 72% accept the necessity of pressure sensors, mounted on the furniture for positioning. The complex manner of information collection gives an opportunity to compensate for the less obtrusive way of non-permanent video camera use.

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