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Context-Aware e-Health Services in Smart Spaces

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Abstract

Résumé abrégé : Dans cette thèse, nous proposons un nouveau système e-santé sensible au contexte pour les sujets âgés, dépendants et isolés. Le système surveille et suit les activités de la vie quotidienne (AVQ) de la personne tout en considérant les standards les plus utilisés en gériatrie pour l'évaluation du niveau de dépendance tel que le modèle SMAF. Le cadre de travail proposé offre automatiquement de nombreux services adaptables tels que la collection d'informations pertinentes et contextuelles et l'évaluation de l'état de santé en se basant sur le niveau de dépendance. Les approches proposées permettent d'apprendre le mode de vie des sujets en se basant sur l'accomplissement des AVQ et la détection des changements de comportement qui peuvent représenter un risque pour la personne. Pour se rapprocher de la vie réelle, nous avons généré des longs scénarios réalistes en définissant un modèle Markovien. Concernant la prédiction du comportement, nous proposons une nouvelle approche basée l'extension du modèle GM (1,1). Les performances de notre proposition sont évaluées et comparées avec les approches traditionnelles de suivi continu en considérant différents scénarios et profils de sujets. Les résultats révèlent que notre système offre un suivi efficace des sujets qui optimise la consommation des ressources du système en termes de calcul, énergie et réseau. Avec un minimum de volume de données collectées et traitées et un minimum de ressources utilisées, notre système réussit à assurer un suivi avec une précision élevée de l'évaluation du niveau de dépendance, d'apprentissage du comportement, de prédiction des conditions de santé et de détection de situation anormales.

Mots-clés : e-santé, AVQ, personnes âgées, contexte, dépendance, surveillance.

Abstract: In this thesis, we propose a new e-health monitoring system for elderly, dependent and isolated persons living alone. We provided a better understanding of the monitored person's context. We develop a context-aware framework for monitoring the person's activities of daily living (ADL) and consider the most famous scales applied in the dependency evaluation models used in the geriatric domain such as the Functional Autonomy Measurement System (SMAF). The proposed adaptive framework offers several services such as the collection of high relevant and contextual data and an evaluation of the health status (i.e. dependency level) of persons. The proposed approach allows learning the human's lifestyle regarding the achievement of the ADL and the detection of the behavioral changes that may represent a risk for the monitored person. In order get closer to real-life situations, we use a Markovian-based model built for generating long term and realistic scenarios. For the behavior detection and prediction, we propose a novel forecasting approach based on the extension of the Grey theory GM (1, 1). The performances of the proposed system are evaluated and compared to traditional monitoring approaches within different scenarios and persons' profiles. The results of our evaluations reveal an efficient monitoring that optimizes the system resources in terms of computing, energy consumption, and network. With a minimum of sensing data, our system succeeds to ensure a high accuracy regarding the evaluation of the person's dependency, behavioral patterns learning, prediction of the health condition, and the detection of abnormal situations.

Keywords: e-health, ADL, the elderly, context, dependency, monitoring.

Résumé

L'un des objectifs des maisons intelligentes de santé (MIS) est d'anticiper toute détérioration de l'état des sujets afin d'éviter les risques de complications majeures. En outre, une MIS devrait maintenir le niveau de dépendance et éviter autant que possible le recours aux établissements de santé. Ainsi, les coûts médicaux, le temps des interventions et les tâches des soignants se verront optimisés grâce aux nouvelles technologies. Pour garantir le succès des systèmes de surveillance de santé, il est crucial d'assurer une maîtrise efficace du contexte de la personne surveillée. Cela correspond à la catégorie des systèmes informatiques sensibles au contexte. Ici, le contexte se réfère à l'ensemble des processus continus qui acquièrent automatiquement tout type d'information relative à la personne et qui est en mesure de fournir et d'adapter les services en conséquence. Pour les systèmes d'aide à la dépendance, le but est de surveiller et d'évaluer les capacités fonctionnelles de la personne par rapport à la réalisation des activités de la vie quotidienne (AVQ) [8]. De tels systèmes sont efficaces lorsqu'ils exploitent une bonne connaissance du comportement humain, identifient le comportement normal, sont capables de détecter les anomalies, et enfin de prédire les états futurs. Le contexte des personnes âgées ne peut pas se limiter à un simple niveau de données brutes acquis par les capteurs. En effet, il est nécessaire d'enrichir cette connaissance en appliquant une intégration de données de haut niveau afin d'en dégager une nouvelle forme de connaissance contrôlée et optimale.

La plupart des travaux existants dans l'e-santé ont été conçus indépendamment des conditions et exigences réelles des établissements de santé. En outre, dans la plupart des études, la motivation derrière la sélection d'un sous ensemble d'activités humaine n'est pas fournie [9] et le contexte de la personne âgée nécessite encore plus d'amélioration. La majorité des approches de surveillance de santé ont tendance à appliquer un traitement inconditionnel sur toutes les données collectées. Cette approche figée de surveillance continue engendre une consommation importante des ressources et ce, quel que soit le contexte de la personne. L'adoption de telles approches présente plusieurs problèmes tels que la saturation du réseau informatique, les erreurs de transmission de données, une consommation d'énergie inutile, et des coûts informatiques importants. On note aussi l'absence de priorités dans le traitement et la prise de décisions qui devraient être pertinentes et rapides en particulier en situation d'urgence. De plus, la mise en œuvre de ces approches nécessite généralement un apprentissage lourd pour maitriser et détecter le comportement et le contexte de la personne. A travers cette thèse, nous nous focalisons sur le suivi des personnes âgées et dépendantes tout en essayant de résoudre les inconvénients des études existantes.

Nous visons à améliorer l'efficacité des systèmes de surveillance de santé pour les personnes dans un environnement intelligent tout en maintenant un lien étroit avec les méthodes médicales existantes, comme les modèles utilisés dans le domaine de la gériatrie. Notre objectif principal est de fournir des services e-santé basés sur une évaluation automatique et homogène des besoins de la personne en matière de soins et de confort. L'amélioration de la connaissance relative au contexte des personnes surveillées vise à fournir des services qui répondent parfaitement au contexte identifié et aux besoins réels. Ceci passe par la réponse aux questions suivantes : qu'est ce qu'il faut collecter comme information, quand et comment surveiller, rassembler et analyser les données liées au contexte d'une personne donnée. Le système ciblé doit fournir un cadre adaptatif et contextuel pour le système de surveillance e-santé. Ce cadre contribue à faciliter l'intégration des services e-santé dans les MIS et les établissements de santé. Le cadre de travail proposé est capable d'apprendre le comportement de la personne, d'évaluer son niveau de dépendance, d'éviter les détériorations de l'état de santé, d'anticiper les complications majeures, et de fournir des services e-santé en temps réel tout en étant sensible au contexte pour prévoir les conditions futures. Une surveillance efficace permet d'identifier les fréquences optimales de collecte de données et assure une utilisation modérée des ressources tout en garantissant une évaluation fiable de la dépendance des sujets surveillés. L'optimisation des ressources tient compte de plusieurs dimensions comme le temps de calcul, le trafic réseau et la consommation d'énergie. Une des exigences considérées et de veiller à fournir une grande précision pour détecter des situations anormales et inhabituelles, quel que soit le niveau de dépendance de la personne. Le cadre proposé se base sur des méthodes appropriées pour détecter et prédire le comportement humain avec de courtes périodes d'apprentissage et une détection des données à minima.

Dans cette thèse, nous discutons de nouvelles méthodes pour améliorer l'autonomie des sujets dépendants afin de proposer un système e-santé qui surveille et évalue le comportement des sujets vis-à-vis des AVQ. Nous examinons les capacités des modèles gériatriques afin de savoir lesquels adopter dans une architecture sensible au contexte et d'en tirer profit pour le suivi des activités par des services e-santé. Différents algorithmes de surveillance sont étudiés en utilisant plusieurs analyses statistiques et modèles mathématiques de prédiction. Nous effectuons des expérimentations sur de nombreux scénarios testés avec des jeux de données synthétiques, générés par des méthodes statistiques. Ces expérimentations diverses ont pour objectif d'évaluer les performances du système proposé, de vérifier la validité et l'adaptabilité des algorithmes utilisés, de mesurer l'efficacité de la sélection des fréquences de détection d'activités et enfin d'évaluer la précision des prédictions concernant l'évolution des états de santé des sujets.

Ce travail comporte une étude exhaustive des récents systèmes et applications sensibles au contexte dans l'e-santé. L'objectif est de mettre en évidence les exigences, les technologies et les défis présents et futurs liés au développement des MIS dans un environnement intelligent. Nous fournissons un ensemble de recommandations afin de cerner les problèmes à aborder pour une amélioration des services contextuels pour les sujets dépendants. Nous présentons en détail les principaux composants importants requis dans les système de MIS : la détection, la communi-

cation et le traitement. De plus, nous présentons une image consolidée des fonctions et services les plus importants offerts par les MIS pour le suivi et la détection du comportement humain, y compris les concepts, les approches et les méthodes de traitement. Dans cette étude approfondie, nous identifions les principales faiblesses des systèmes e-santé existants. En particulier, nous pointons le manque d'une véritable compréhension du contexte de la personne, lié à son état de santé et au degré de réalisation des AVQ. Nous avons également observé que les systèmes existants ont été proposés indépendamment des conditions réelles des établissements de santé et des outils utilisés. En effet, on constate un manque de lien fort entre les données surveillées et l'évaluation de l'état de santé tel qu'il est appliqué par les soignants notamment avec l'ignorance du niveau de dépendance des sujets.

Aucune des approches actuelles ne considère systématiquement le contexte des sujets en terme d'état de santé et de comportement tel qu'il est défini dans les modèles de gériatrie. Les systèmes e-santé existants pour les sujets dépendants ont été définis en fonction de la disponibilité des capteurs de détection plutôt que sur la base de connaissances médicales ou gériatriques. Les efforts visant à améliorer la qualité des soins à l'aide des technologies permettant un espace intelligent restent ad hoc et ne fournissent pas les résultats souhaités. De plus, les approches traditionnelles de surveillance de la santé et les systèmes de vie assistée sensibles au contexte ont tendance à gérer toutes les données détectées sans distinction avec un traitement inconditionnel. La plupart appliquent un suivi continu qui exige que les flux de données soient disponibles tout le temps, quel que soit le contexte de la personne. Plusieurs méthodes pour la détection et la reconnaissance du comportement humain dans les environnements intelligents exigent des quantités importantes de données et un lourd apprentissage afin de gérer le contexte du sujet.

Il est important que les systèmes e-santé soient liés à une base de connaissance médicale appropriée qui devrait être exploitée pour maitriser le changement du comportement suivi et le mettre en corrélation avec le changement d'état de santé des sujets. La compréhension du contexte du sujet permet de fournir des services e-santé adaptables, personnalisables, et affinés pour répondre aux besoins réels qui sont changeants dans le temps. Ceci permet également de faciliter l'intégration des nouveaux systèmes proposés dans les établissements de santé. Dans un espace intelligent, les services e-santé de surveillance et de suivi des personnes nécessitent une description claire de la nature des activités humaines et de leurs caractéristiques. Dans cette thèse, nous avons décrit le contexte de la personne en relation avec la réalisation des AVQ telles qu'elles sont définies en gériatrie avec les échelles d'évaluation de la dépendance. Nous avons décrit une taxonomie des activités et de leurs caractéristiques de manière détaillée afin de rendre les nouveaux systèmes e-santé plus efficaces.

Dans cette thèse, nous améliorons la connaissance du contexte de la personne surveillée relative à la réalisation des AVQ. Nous examinons en détail les modèles et échelles d'évaluation des personnes dépendantes et nous mettons l'accent sur la satisfaction des besoins des sujets par rapport aux services e-santé qui peuvent être proposés dans un espace intelligent. Une partie de ce travail a été consacrée à l'étude approfondie et l'évaluation des modèles les plus utilisés en gériatrie notamment le modèle AGGIR (utilisé en France) et le modèle SMAF (utilisé au Canada). Nous examinons la compatibilité entre les deux modèles, en particulier en termes d'activités (éléments), de résultats d'évaluation, et de classification des sujets sous forme de profils et groupes. Grace à cette étude, nous identifions les faiblesses, et parfois les contradictions, de ces modèles en vue de les améliorer pour être ensuite exploités dans une architecture e-santé sensible au contexte.

Grace à un nouvel algorithme d'appariement que nous avons proposé et de nombreuses expérimentations, notre étude montre clairement que les deux modèles (SMAF et AGGIR) ne peuvent satisfaire les exigences requises en termes d'efficacité et de fiabilité des plateformes e-santé. Les simulations effectuées ont été traitées sur un volume de données très important : vingt mille milliards d'évaluations. Chaque évaluation traitée représente une personne ayant un certain profil de dépendance. Les résultats permettent de constater que les modèles existants sont inadéquats et ne sont pas efficaces pour donner une évaluation précise de la dépendance des personnes âgées. Par conséquent, les modèles existants, tels qu'ils sont définis, ne peuvent refléter le contexte réel de la personne. A titre d'exemple, le même sujet peut être considéré comme autonome en utilisant un modèle et considéré comme une personne dépendante dans un autre modèle.

Par conséquent, afin de réduire davantage le taux d'erreur dans les modèles d'évaluation existants et de concevoir un écosystème e-santé efficace, il est important d'améliorer la qualité et les performances de l'évaluation de la dépendance. Nous considérons, entre autres, les problèmes de validité concernant les évaluations des activités et l'évaluation inutile de certaines activités dans les situations de dépendance sévère. Dans un cadre e-santé, associer des périodes de validité à chaque activité surveillée et évaluée rend le système plus sensible au contexte. En effet, afin d'assurer des services efficaces dans le temps, la validité d'une évaluation doit dépendre du type d'activité et de la nécessité de mise à jour avec un seuil bien déterminé. Afin d'optimiser le suivi automatique, certaines activités peuvent ne pas être surveillées continuellement. Par exemple, en cas de dépendance sévère, il n'est pas nécessaire de surveiller les soins de toilette en permanence. L'accent doit être mis sur les activités qui affectent directement la vie des sujets et qui peuvent déclencher certains services requis en fonction des profils.

Afin de gérer les variations de profil des personnes suivies, nous proposons une modélisation du comportement quotidien qui permet de générer des scénarios associés qui sont riches et variés. Nous définissons une nouvelle stratégie de génération de scénarios, basée sur un modèle markovien afin de considérer différents profils de dépendances. L'objectif est de générer des séquences d'activités qui soient riches et réalistes, d'une personne avec ou sans handicap et pour une longue période. La conception d'un modèle markovien pseudo-variable a permis de générer des scénarios réalistes à long terme. La génération de scénarios AVQ fournit des données suffisantes pour aider à la conception et aux tests approfondis des approches utilisées dans les systèmes e-santé. Ces données peuvent être directement utilisées avec des implémentations réelles de MIS (sans mettre en péril de vrais sujets) permettant des tests avec une grande flexibilité.

En se basant sur la bonne maitrise acquise pour la gestion et l'évaluation du contexte des sujets ainsi que sur la possibilité d'étudier de nombreux scénarios de la vie quotidienne, nous avons proposé un système de suivi adaptatif et contextuel qui s'attaque aux inconvénients et faiblesses des solutions e-santé existantes. Notre objectif est d'améliorer l'efficacité de la surveillance e-santé tout en maintenant un lien étroit avec les méthodes et les connaissances médicales existantes notamment avec les modèles utilisés dans le domaine gériatrique et l'utilisation optimale des ressources telles que l'énergie, le réseau et le traitement des données. Notre approche permet de déterminer quel type d'information il faut capturer, à quel moment, et comment le système doit procéder pour suivre le sujet et surveiller son état, collecter et analyser les données liées à son contexte et ses variations. La détection et l'analyse des activités quotidiennes sont sensibles au contexte dans le sens où elles sont liées au type d'activité exécutée, sa complexité, sa récurrence et la durée requise pour l'accomplir.

Nous avons développé une architecture adaptée au contexte pour les systèmes de surveillance et de suivi des personnes dans un environnement connecté et intelligent. Le cadre de travail proposé se repose sur un ensemble flexible de capteurs et est capable d'adapter dynamiquement son mode de surveillance en fonction du contexte de la personne, de son historique et de la nature des activités surveillées. En plus de la connaissance du comportement de la personne suivie, la consommation d'énergie habituelle pour chaque activité a été exploitée pour affiner cette connaissance. Le système résultant emploie une analyse statistique et un modèle de prédiction mathématique et ne nécessite que des phases courtes d'apprentissage et une quantité minimale de données collectées. Contrairement aux solutions existantes et aux systèmes traditionnels de surveillance e-santé, nos approches proposées utilisent un schéma de traitement conditionnel intelligent pour optimiser les ressources du système et adapter leur utilisation au contexte de la personne. Dans notre système, le profil de la personne (comprenant le niveau de dépendance et l'historique) représente la clé essentielle pour adapter les capteurs à une fréquence de détection optimale afin de ne traiter que des données jugées pertinentes. Le cadre proposé est capable d'apprendre le comportement humain, d'évaluer automatiquement la dépendance de la personne, d'anticiper la détérioration de l'état de santé avant d'éventuelles complications, et de prédire les futures conditions de santé. En outre, le système a permis d'optimiser l'utilisation des ressources (traitement, trafic réseau et énergie) sans compromettre la qualité du service e-santé et avec la possibilité de détecter les situations à risque.

Afin d'implémenter la prédiction dans notre système, nous nous sommes basés sur un modèle dénommé `Grey Model(1, 1)`. L'objectif est de pouvoir détecter les changements de comportement de la personne et de prédire l'évolution des conditions de santé. Le modèle défini assure une prédiction de l'état de santé des sujets en fonction du comportement relatif à l'accomplissement des AVQ tout en utilisant la consommation d'énergie comme indicateur qui reflète bien les activités de la personne dans un espace connecté.

La prédiction `GM(1, 1)` utilise la projection de la tendance croissante ou décroissante relative à la réalisation de plusieurs activités de la vie quotidienne. Celle-ci sert à prédire le futur état de santé. L'approche proposée pallie les inconvénients des systèmes e-santé existants ainsi que ceux d'autres approches de prédiction qui nécessitent le traitement de masses importantes de données d'apprentissage. Notre système proposé fournit une attention proactive en utilisant uniquement les données

pertinentes et peut déclencher des notifications vers l'extérieur (par exemple à un centre de soins) si une forte probabilité de déclin est détectée.

En somme, avec une gestion efficace du contexte des sujets couplée à une approche adaptative et prédictive, le système présenté dans cette thèse réussit, avec un apprentissage court et un volume collecté minimal de données, à assurer les principales fonctionnalités initialement visées. Ces fonctionnalités sont principalement : une grande précision concernant l'évaluation de la dépendance de la personne, un apprentissage des modèles comportementaux, une prédiction des futures conditions de santé avec une grande précision pour détecter les anomalies. Dans un espace intelligent, notre système emploie des fréquences optimales de collecte d'informations permettant une utilisation modérée des ressources. L'optimisation des ressources concerne de nombreuses dimensions telles que le traitement des données (collecte de données pertinentes et contextuelles), le trafic réseau et la consommation d'énergie.

Par exemple, dans la surveillance adaptative avec différents profils de personnes, la fréquence de détection ()identifiée X_2) permet de réduire de 48,3% la consommation d'énergie, de 49,3% le trafic réseau et nécessite un traitement qui concerne seulement 54,3% des activités quotidiennes. En traitant un très faible volume de données, le système proposé réussit à obtenir une précision parfaite (100%) pour l'évaluation du niveau de dépendance des personnes (c.-à-d. la détection d'un déclin). L'approche prédictive proposée a permis d'assurer une grande précision dans la détection de comportements anormaux pour tous les niveaux de dépendance des personnes surveillées avec une précision de 100% en mode de suivi élevé (fréquence X_2), de 95.8% en mode de surveillance moyenne (fréquence X_3) et 91,9% en mode minimum de surveillance (fréquence X_4).

CHAPTER 1

Introduction

Contents

1.1 Background and Motivation

Population aging is happening more quickly than in the past. According to the United Nations Population Fund (UNFPA) projections [1], the number of people aged 60 or older was 205 million in 1950 and increased to almost 810 million by 2012, and will rise to 2 billion marks in 2050 globally (see Figure 1.1). For instance, around 242 million persons aged 60 years or more in Europe countries. Meanwhile, a report issued by the World Health Organization (WHO) stated that there is a shortage of about 7.2 million healthcare workers in 2013, and the figure is estimated to reach 12.9 million by 2035 [10]. Thus there is no balance with the number of the healthcare workforce, which in turn widens the gap between supply and demand in the healthcare domain.

A significant proportion of elderly population suffers from age-related health issues such as Alzheimer's disease, dementia, diabetes, cardiovascular disease, osteoarthritis, and different chronic diseases. The progressive decline in physical and cognitive skills coupled with these common diseases prevents elderly and dependent persons to live independently in their home and to performing basic activities of daily living (ADL). Moreover, the human daily behavior could be heavily influenced by the subject's diseases. Health care quality of service and social cost are negatively affected by the aging population. Increasing the number of care providers to handle the projected growing number of elderly population is not a realistic solution.

The recent advances in ambient intelligent technologies have resulted in a rapid emergence of intelligent environments. The intelligent environments and specifically

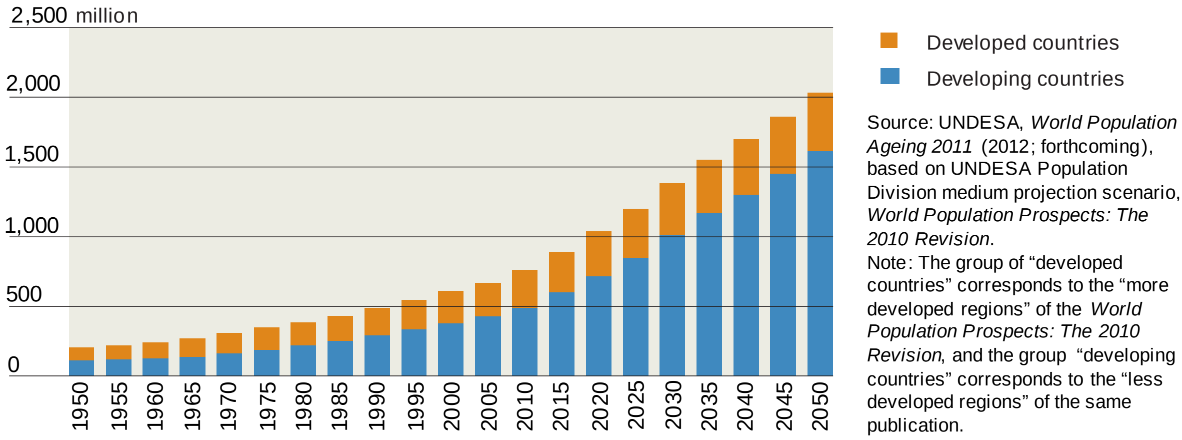


Figure 1.1 – Projections the number of people aged 60 or over [1]

smart home environments have become an important research topic in recent years. Apart from adding more care providers, smart home environments expected to play a significant role to help elderly and dependent people and alleviate the burden of health care workers.

Moreover, the adoption of information and communication technologies (ICT) within the healthcare sector led to the concept of *electronic health* (e-health) [11]. The term e-health was defined in [12] as "an emerging field in the intersection of medical informatics, public health, and business, referring to health services and information delivered or enhanced through the Internet and related technologies. In a broader sense, the term characterizes not only a technical development, but also a state-of-mind, a way of thinking, an attitude, and a commitment for networked, global thinking, to improve health care locally, regionally, and worldwide by using information and communication technology".

Health Smart Home (HSH) represents a pervasive healthcare system in a smart environment and gained a high significance in recent years. HSH integrates several functionalities into the same coherent system. These functionalities vary from the simplest home automation, such as using light and motion sensors, to ambient intelligent technologies, such as sensing, communication, and computing [13]. HSH for elderly and dependent persons provides individual healthcare and social services such as nursing, rehabilitation, and health assistance in their own place. In particular, HSH systems aim to monitor and evaluate the person's health condition and their behavior in performing daily life activities, make healthcare services more sustainable, enable elderly to live more independently and enhanced quality of life at their evolving space (e.g. home, city, etc.). Specifically, these systems consider the monitoring of illness, handicap, and dependency in order to provide timely e-health services that meet the person's context and personalized needs in smart environments. The objective is to detect any deterioration regarding the person's health and prevent major complications. Moreover, the system aims to maintain the dependency level and avoid, as long as possible, the delays of recourse to healthcare institutions (e.g. nursing homes and hospitals). Thus, the system reduces medical costs, time, and facilitates the tasks of health caregivers through technology.

Being able to identify the context of monitored persons is crucial to the success of proposed health monitoring systems. The context-aware paradigm in healthcare refers to the set of continuous processes that automatically acquire the person's information (e.g. behavioral, physiological, and environmental information), and are able to provide and automatically adapt the services accordingly. Context-aware assisted living systems must have a global and full visibility of the person's context. This visibility includes a good understanding of the person's lifestyle in performing the daily activities and detecting anomalies in behavior. Another additional functionality is the ability to predict the future health condition and anticipate risky situations.

1.2 Overview of the Research

Context-aware health smart home and assisted living systems for elderly target monitoring and evaluating the person's functional abilities regarding the correct achievement of the ADL activities [14] [8]. Such systems are effective when they have a good knowledge of the human's daily behavior including the ability to understand the normal behavior, detect the abnormal situations, and predict the health conditions of the subjects. The context of elderly can not be confined to the simple level of raw data acquired by sensors. It should be enriched the application of a high-level data extraction, integration, and inference toward a new knowledge that can be controlled using several approaches and techniques.

Most of the existing researches in e-health systems operate in isolation from the real requirements of the healthcare institutions. In addition, in most studies, the motivation behind the selection of the activities is not provided [9], and the context of elderly person still need more improvement. Most of the health monitoring approaches tend to apply unconditional processing on all the collected data. This fact results in a continuous monitoring approach which is resource intensive whatever the person's context and profile. The adoption of this approach causes several issues such as the collapse of the network, data transmission failure, energy consumption, important computational cost, and loss of priorities in processing and making decisions that should be relevant and quick especially in emergency situations. As well, these approaches typically require substantial amounts of training data to learn and detect the human's behavior and surrounding context. The current research of this thesis primarily addresses the elderly monitoring and tackles the drawback in the existing studies of health monitoring systems.

1.3 Research Objectives

The recent advances in ambient intelligent technologies including sensing, communications, and computing have made it possible to evaluate the human's daily behavior in smart environments. However, although a variety of sensor technologies are widely available today, existing e-health services systems do not satisfy the desired requirements and lack of selecting related data that reflect the real context. The determination of such knowledge from the huge amount of sensor data is a complex task in context-aware systems. Due to the complexity of the human's behavior, extracting a meaningful knowledge for the context of the monitored person and detecting the health condition represent open research challenges [15] [16].

Our objective is to improve the effectiveness of the e-health monitoring systems for elderly and dependent persons in a smart environment and keep a strong link with existing medical methods such as the models used in the geriatric domain. In this thesis, we investigate methods for supporting independent living of the elderly by monitoring and evaluate their behavior regarding the performance of activities of daily living. We investigate the medical knowledge and its ability to be adopted in HSH for supporting independent elderly. We propose a new adaptive and predictive context-aware monitoring system. The research aims to provide a better understanding of the person's context regarding the daily activities and define the approaches needed to detect behavioral patterns and abnormalities. We make more precise inferences about the situation of persons and define a way to predict future health condition.

In order to reach the aim of this research, the following objectives are presented:

- Provide e-health services based on an automatic and homogeneous evaluation of the person's needs in terms of healthcare.

- Improve the knowledge about the context of monitored persons in order to provide them with e-health services that meet their context and real needs

- Determine what, when and how to monitor, gather and analyze data related to the person's context and profile.

- Develop an adaptive and context-aware framework for e-health monitoring system. The framework helps to facilitate the integration of e-health services in a smart space with health institutions. The framework learns the person's behavior, evaluates his the person's degree of dependency, prevents deteriorations in health before major complications, provides timely and context-aware e-health services, and predicts future health conditions.

- Ensure an efficient sensing of the surrounding environment with optimum frequencies and combine the optimization of used resources while providing a reliable evaluation regarding the observed dependency of monitored subjects. Resources optimization considers several dimensions like computing, network traffic, and energy consumption. Moreover, we aim to avoid the exaggerations of the existing dependency evaluations that consider all the daily activities at whatever the person's degree of dependency even in severe ones.

- Provide a high accuracy in detecting abnormal and unusual situations whatever the level of the person's dependency.

- Identify and develop appropriate methods to detect and predict the behavior with short training periods and a minimum of sensed data. Such methods should not negatively impact the monitoring quality and the system's ability to detect abnormalities.

It is worth mentioning, the concept of person's context presented through the manuscript is regarding the context of user's autonomy as evaluated through the current geriatrics scales and does not consider the ambient context of the user as a whole. Moreover, the optimization of the health monitoring is only limited to the management of the technical resources (bandwidth, energy consumption). The reduction of intrusiveness in the user's life is only suggested through the reduction of the number of information transferred. Furthermore, all the results presented in this work were obtained from simulations on data produced by a simulating machine with the objective of producing realistic scenarios for a long period of monitoring.

1.4 Contributions of the Thesis

The major contributions of this thesis are stated as follows.

- We presented a comprehensive study of context-aware computing in the healthcare field for subjects like elderly and dependent persons. We reviewed the current state of the art related to health monitoring systems. We presented a consolidated picture of the most important functions and services offered by HMS for monitoring and detecting the human's behavior including concepts, approaches, and processing techniques. We discussed the main challenges and weaknesses and identified the recommendations to improve future smart health monitoring systems.

- We provided a better understanding of the context of the monitored persons, improve the knowledge of the human activities of daily living that should be monitored in such efficient e-health systems. We clarified and evaluated how such knowledge affects the performances of the monitoring system.

- The study clearly showed how the existing and most currently used health models (SMAF and AGGIR) are inadequate and not efficient to give an accurate assessment of the person's health condition and degree of dependency. We identified how such models need more improvements to fulfill the requirements of efficiency and reliability of e-health services.

- We developed an adaptive context-aware framework for e-health monitoring system for smart environments. The framework is capable to dynamically adapt the monitoring mode depending on the person's context, his history, and the nature of monitored activities.

- We succeeded to propose a system which requires short training periods and a minimum amount of sensed data in order to identify the human behaviors and health conditions (in terms of dependency levels) by using a statistical analysis and mathematical prediction.

- We define a daily life behavior modelization and generate dataset series. We defined a new approach for a realistic human scenario generation which considered the person profile. The approach is based on the Markovian model and allows to provide a tool which generates a rich and realistic sequence of activities of a person with or without disabilities and for a long period.

- We developed a forecasting technique using the Grey Model theory, using GM (1, 1) model, to detect the human behavior changes and predict the evolution of the health conditions. We were based on the person's behavior and the idea that the energy consumption reflects well the activities of the person. GM (1, 1) prediction uses the increasing or decreasing trend in achieving several activities of daily living which, in turn, is used to predict the future health conditions. Extensive experimentations are performed to validate our results.

1.5 Thesis Roadmap

The remainder of the thesis contains six chapters organized as follows:

Chapter 2: Health Smart Home
This chapter presents a review of health smart monitoring systems for individuals, especially for elderly and dependent persons. The chapter highlights the requirements, technologies, design, modeling, and challenges in the development of HMS in smart environments. The chapter presents a consolidated picture of the most important functions and services offered by HMS for monitoring and detecting the human's behavior including concepts, approaches, and processing techniques. Moreover, the chapter provides an extensive, deep analysis, and evaluation of the findings in the area of e-health systems. Finally, we present the main challenges and open issues facing the smart health monitoring field, as well as the weaknesses and recommendations to improve future systems.

Chapter 3: Health Measurements for the Elderly
This chapter describes the person context regarding the achievement of the activities of daily living as defined in the geriatric field and dependency evaluation models. The Chapter reviews the most commonly used measurement models in the domain of e-health and dependency evaluations and includes a description of the most important concepts in each model such as items (activities) and evaluation methods. The Chapter provides a better knowledge about the target activities and their characteristics for the subjects evolving in space toward a proper sensing and framework design of monitoring.

Chapter 4: Elderly's Context and Dependency Models
In this chapter, the context of monitored persons is considered by studying and comparing the existing health models used in the evaluation of dependent subjects. The Chapter discusses the compatibility between the most currently used models which are SMAF and AGGIR. The models' analysis includes the considered person's activities and the results of classification and evaluations. A matching algorithm between models is proposed and an important simulation is discussed. This simulation considers a huge amount of data (twenty trillion of possible situations). The Chapter provides a better understanding of the context of the monitored person with a

set of activities of daily living identified for an efficient e-health system. We show how such knowledge affects the performances of health monitoring system.

Chapter 5: Context-Aware Adaptive Framework
In this chapter, an adaptive and context-aware framework for e-health monitoring system is proposed. The framework aims to keep a strong link with existing medical knowledge in order to facilitate the integration of e-health services in smart spaces with health institutions. Based on the knowledge provided in the previous Chapter, we define three approaches that consider the nature of the monitored activities, the person's profile and the relationships between activities. The discussed approaches are based on a smart conditional processing scheme (request-driven monitoring scheme) to optimize the system resources and adapt their use based on the context of the monitored person. In addition, a new strategy, based on the Markovian model, is defined for generating long-term realistic scenarios. The proposed adaptive system in this Chapter determines *what*, *when* and *how* the e-health system should monitor, gather and analyze data related to the person's context.

Chapter 6: Health State Prediction and Behavioural Change Detection
In this chapter, a new forecasting technique using the Grey Model GM (1, 1) is developed in order to detect the human behavior changes and predict the evolution of the health conditions. The proposed predictive model uses the framework and conditional processing scheme discussed in the previous Chapter. We conclude that the proposed predictive and e-health monitoring system is able to learn the person behavior patterns, ensure high accuracy of dependency evaluation, predict future health condition, and provide high accuracy to detect the abnormalities by analyzing a minimum amount of sensed data with a short period of training.

Chapter 7: Conclusion and Perspectives
This chapter provides the conclusions of this thesis and presents some perspective and future research for the e-health monitoring of persons in the smart environments.

Part I

State of the Art

CHAPTER 2

Health Smart Home

Contents

2.1 Introduction

The recent advances in ambient intelligent technologies including sensing, communications and computing have resulted in a rapid emergence of smart environments. Among these, the so-called *Health Smart Home* (HSH). HSH represents a context-aware health monitoring system in a smart environment which have gained considerable interest in recent years. HSH emerged as a promising solution to address the problem of increasing aging populations with the ability to provide them with e-health services that match their context and real needs.

In order to achieve this benefit, challenging series of procedures and mechanisms are required. This involves the remote monitoring (data acquisition about the person, his environment, etc.), the communication technology (reliability of data transmission in real-time), an intelligent processing system (analysis, making relevant decisions, etc.) and then providing context-aware services. Consequently, to face these challenges, current solutions need further efforts to design a new efficient health monitoring system for HSH.

By examining the current literature in this field, we can observe that the health monitoring systems (HMS) can not be proactive to help persons with required assistance and services unless a full set of contextual information becomes available. Indeed, the success of such systems lies in the consideration of the person's context as a sound basis to collect and process data and to distribute context services. The application of the context-aware paradigm in healthcare refers to the set of continuous processes that automatically acquire a person's information (e.g. behavioral, physiological, and environmental), and are able to provide and adapt the services accordingly. The context of elderly can not be confined to a simple level of data acquired by sensors but should be enriched by extracting a high-level data integration and inference toward a new knowledge controlled using several approaches and techniques. Context-awareness helps for a better understanding regarding the health conditions of the monitored person, identifying the behavior patterns and making more precise inferences about the situation of persons and their environment.

In this Chapter, we present a comprehensive study of context-aware computing in healthcare systems for elderly. The objective is to highlight the requirements, technologies, methods, and challenges in the design of HMS in smart environments. We present a set of guidelines that would help to understand the issues that need to be addressed in order to improve healthcare services for this category of individuals. The layout of this Chapter is organized as follows: Section 2.2 describes the concept of context-aware in healthcare systems. The main important components required in HMS (sensing, communications and processing system) are identified in detail in Sections 2.3 and Section 2.4. A consolidated picture of the most important functions and services offered by HMS for monitoring and detecting human's behavior including concepts, approaches, processing technique is presented in Sections 2.5, 2.6 and Section 2.7. In Section 2.8, a survey of the recent research and evaluate the state of the art for healthcare applications and monitoring systems is provided. In Section 2.9, some research challenges for future healthcare applications are discussed. The conclusions are drawn in in Section 2.10.

2.2 Context-Aware in Healthcare

Many definitions of the *context* concept have been proposed in the literature. According to [17], the context represents *any information that can be used to characterize the situation of an entity. An entity includes a person, a place or an object.* Authors in [18] have provided a distinction between two types of information: *raw data* and *context information*. Data raw, also called *low-level* context, is unprocessed data taken directly from the source such as a sensor. In e-health, such data may represent the person's vital signs and environmental parameters (e.g. temperature, humidity, and sound), person movements and profile, etc. Note that the acquired raw data can be worthless if it is not well interpreted and understood by the HMS. The second category of information is the *context information* which, in spite of the first category, is generated by processing raw data. For instance, by applying a consistency validation or metadata enrichment. It refers to extract high-level information and knowledge such as regarding the behavior patterns, health cases, person's activity, etc.

The context plays a significant role during the health monitoring mainly due to two reasons. First, in a smart environment, evaluating the monitored subjects regarding their health conditions and their performances in achieving their activities of daily living (ADL) relies heavily on the understanding of the sensed context of subjects. For instance, changes in vital signs data should be correlated with a better understanding of the current user's situation. Example, the system's interpretation about the cardiac activity should be linked to the nature of the current activity which is substantially different for the *housekeeping* activity compared to the *watching TV* activitiy. A high toileting activity may refer to diabetes risk, high recording of sleep disorders with hepatitis C [19], etc. Second, the context can be useful to make HMS more efficient and optimal. Indeed, in HSH, data of the subject's context (behavioral, physiological, and environmental) are often collected using various sensors and devices. A continuous processing and fusion of such data in HMS require a huge amount of computation. The optimal selection of active sensors and how the data should be operated (collection and analysis of high relevant contextual information) is the core of HMS effectiveness which is highly dependent on the context [20]. Therefore, the context represents a key knowledge source for healthcare systems to provide relevant context-aware services.

Different classes of the context have been defined based on different views, perspectives and considered dimensions used to represent the context. Each context dimension is used to define an elementary piece of related information. For example, the authors in [21] considered location, environment, identity and time. In [22], the context data is collected based on the answers to the following three questions: Where, Who and What? In [23], the context refers to location, identity, activity and time. These dimensions act as the primary layer of the context to characterize a given situation. Then, other related information can be used to refine the description of the context. For example, given a person's identity, we can collect other related dimensions such as phone numbers, addresses, other nearby people in the environment, etc. The primary pieces of the context should answer the following five W's questions Who, What, Where, When, and Why? These questions were identified in [24] as a minimal set of information necessary to understand the context and situations. For instance, identifying the person and his location along with achieving one activity at a specific time could provide useful information in health monitoring systems. The evaluation of the person's conditions will, consequently, depend on the accurate knowledge of the current context. A lying position in the sleeping room at night refers to a normal situation, while the same position in the middle of the day and for a long time could refer to an abnormal situation.

The use of the context concept in computing results in the design of *context-aware systems*. Several definitions of the *context-awareness* term can be found in the literature. In the following, we will only focus on the definitions that give a clear idea about how this concept can be used in health monitoring systems. Context-awareness allows to automatically provide information or take actions according to the user's present context and need [25]. According to [26], the concept refers to applications which are able to monitor inputs from sensing devices and choose the suitable context according to user's need or interests. In [23], a system is qualified as context-aware if it uses the context to provide relevant information and services to the user. Here, the relevance depends on the user's task. In pervasive healthcare systems, context-aware computing systems consider the application's ability to adapt to changing circumstances and respond according to the context of use [27].

Generally, context-aware computing systems are usually designed and implemented for certain purpose and focused on finding solutions for specific problems. Thus, there are no knowing and uniform considerations to build such systems. The essence of the difference between systems lies in the provided degree of awareness. In context-aware systems, this degree is usually called *level* which in turn have been defined using different ways and methods [28] [29]. Therefore, designing an optimal context-aware system for e-health is still an open issue with several challenges. In spite of this complexity, the analysis of hospital-based projects [30] reveals that several efforts have been made in the consideration of context-aware computing in healthcare applications. Nevertheless, there are still many limitations and drawbacks with context awareness e-health services, such as the absence of the recommendations for functional needs of the context, gap between fundamental context representations and actual context awareness prototypes and the difficulty of building an efficient system to simulate the human perspective.

Broadly, context-awareness systems have many components that are responsible for several functions including representation, management, reasoning, and analysis of context information. Different types of contextual information are obtained from various sources (e.g. sensors) which are deployed in the monitoring area network of the HSH. Data models are used to represent and store the context data. Using a high level extraction of contextual information, by interpreting or aggregating context data, provides a clear knowledge about the profile of the monitored person and his environment. Consequently, the system processes the abstracted context for e-health context-aware applications and allows to dynamically determine the person's real needs in terms of assistance and services.

2.3 Overview of Health Smart Homes

Health Smart Homes (HSH) and Healthcare Monitoring Systems (HMS) are an efficient mixture of the integration of ubiquitous computing and communication technologies. HSH is a term that refers to all kinds of technology solutions that aim to assist people with special needs (e.g. patients, elderly and disabled) in their daily life. HSH integrates several functionalities into the same coherent system. These functionalities vary from the simplest home automation (e.g. using light and motion sensors) to ambient intelligent technologies (e.g. sensing, communication, computing, etc.)[13]. From the perspective of the elderly, the home integration of these technologies with the goal of home assistance leads to a more independence and safety in the daily life.

In telehealth perspective, several computing paradigms share similar concepts in order to support the research in this realm: context awareness, ubiquitous computing, embedded computing, pervasive computing, sentient computing and others [30]. In these paradigms, computers are embedded in everyday objects that human beings use or interact with. Several studies and solutions have been proposed to address diverse aspects. In general, these solutions share common goals and general properties. The main objective is to provide a smart environment where the system monitors and evaluates the health conditions of persons and provide them with timely e-health services. In order to achieve this target, there are several enabling technologies that fundamental act as the stepping stones to develop context-aware HSH and Ambient Assisted Living (AAL), as described in several studies such as in [31] and [32]. The used technologies are related to the following main functionalities:

- Sensing: obtain the user physiological, behavioral and environmental data
- Communications: data sources (sensors and actuators) are connected together to the processing and reasoning system which in turn could be connected to other systems.
- Reasoning: aggregating, processing and analysing data, and extract knowledge (high-level context information). The reasoning technology is the essence of smart environments and could be implemented in sensors, servers, etc.
- Acting: automatic actions and feedback initiated by the system (e.g. information, suggestions, guidance). Acting could be local or remote, either

instantaneous (e.g. alarm in emergency situation) or delayed (reminder, recommendations).

Most of the existing pervasive health systems have the ability to interact with different categories of persons (e.g. patients, elderly, and disabled) using one or more types of sensors. Sensors are responsible for data acquisition and are either stationary sensors deployed in the domestic settings or wearable sensors carried by the monitored person. Both of these two categories of sensors gather contextual information of the person in a constant or periodic way. Sensors relay these data through, for instance, an access point or a base station to a home server or portable devices via diffident available network technologies. The home server and/or portable devices are acting as a gateway. The gateway is a common element used in HSH and HMS and is usually seen as the network coordinator that provides remote access and control and acts as the bridge between the local area network (LAN) used in the HSH and the wide area network (WAN) such as the Internet, cellular or fixed telephony networks.

At the application level, the actors of a health monitoring system (patients or health providers) use a graphical user interface (GUI). Depending on the complexity of the system, GUIs can be used in the monitoring and evaluation of the person conditions, the health parameters, and can notify alerts to caregivers in the case of an abnormal detection or an emergency situation. Various parameters and heterogeneous data collected from sensors can be involved such as the environment (e.g. temperature, humidity, and sound detection), movement and location tracking (e.g. gesture and pressure), and vital signs (e.g. heart rate, oxygen saturation, and blood pressure). These data provide a low-level view about the context of the person's health status and his surrounding and living environment. Based on the system architecture, the hardware capabilities (sensing, connection, and gateways) and methods used in processing the data help the system to gain a high-level view of the context. In complex and intelligent applications, the high-level view of the context is used in many aspects such as the classification of diseases, the prediction of the health status, patterns detection of the human behavior, etc. Figure 2.1 shows the general overview of an HMS.

HSHs are based on a common set of components responsible for sensing, communication, and processing data (detailed in next subsections). However, we can differentiate existing systems based on the following three aspects: (i) the target, (ii) the capabilities, and (iii) used methods. First, depending on the target application and population, the difference between existing HSH projects lies in the variation of considering the person needs and requirements which can lead to a small concentration of the context dimensions. Many projects reduce the context to a single parameter and objective. For instance, fall detection and location tracking or the monitoring and evaluation of a single type of daily activity (e.g. sleeping), a certain cognitive disease (e.g. Alzheimer's) or biological disease (e.g. heart disease).

Second, the capability of HSH refers to the ability of processing, storage, communication type, bandwidth, and energy management of the devices used in the sensor network. Based on these capabilities, which increase from the lower to higher layers, the data can be processed at many levels. Overall, the most common structural components of a sensor network used in healthcare monitoring systems are

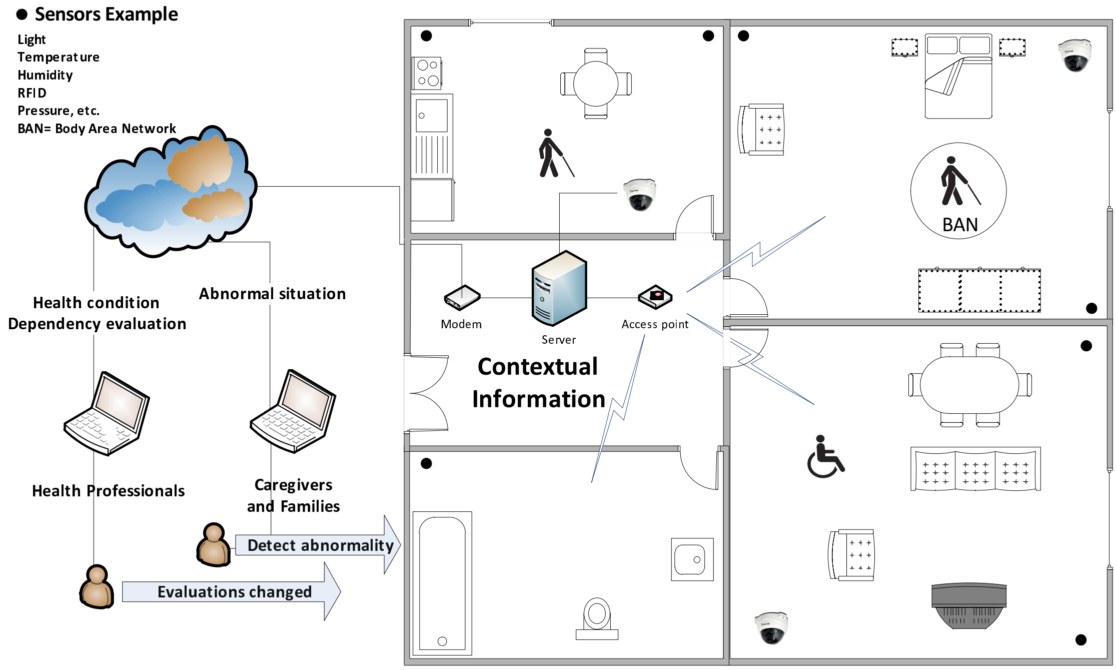


Figure 2.1 – General overview of a health monitoring system. Data, from the continuous sensing, reflects the person's context. HMS provides regular health evaluations to determine the real needs and alert the caregivers in critical situations.

presented in (Figure 2.2). The data collection follows a bottom-up flow, and the information can be processed at many levels. In such structure, raw numeric data are generated by terminal sensor nodes deployed in a designated area. Each sensor node gathers and transmits data directly to a gateway or base station called the sink node (static or mobile sink) which in turn is connected to the gateway. Finally, if it is needed, data reaches the WAN for external exchanges. Sensors and devices in the lower levels perform a certain amount of basic processing on the captured data, which can reduce the amount of transferred data and prevent network congestion. However, due to the hardware and software limitations of used devices in terms of processing, memory, and energy, the majority of data processing is achieved at higher levels. Therefore, the system capabilities represent one of the key aspects which determine the *smartness* of the health monitoring system.

Finally, there are different methods and algorithms that can be used in HSH such as learning-based and reasoning-based approaches. Used methods depend on several considerations such as the amount and nature of collected data (e.g. using a sensor-based or vision-based data), the monitoring methodology, and the application requirements. In the following subsections, we briefly present the most important components required in HMS in terms of sensor systems, communication gateway, and applications.

2.3.1 Sensor Systems

Data acquisition is the first step in the health monitoring environments in which various sources are used to gather the information related to the physical status of

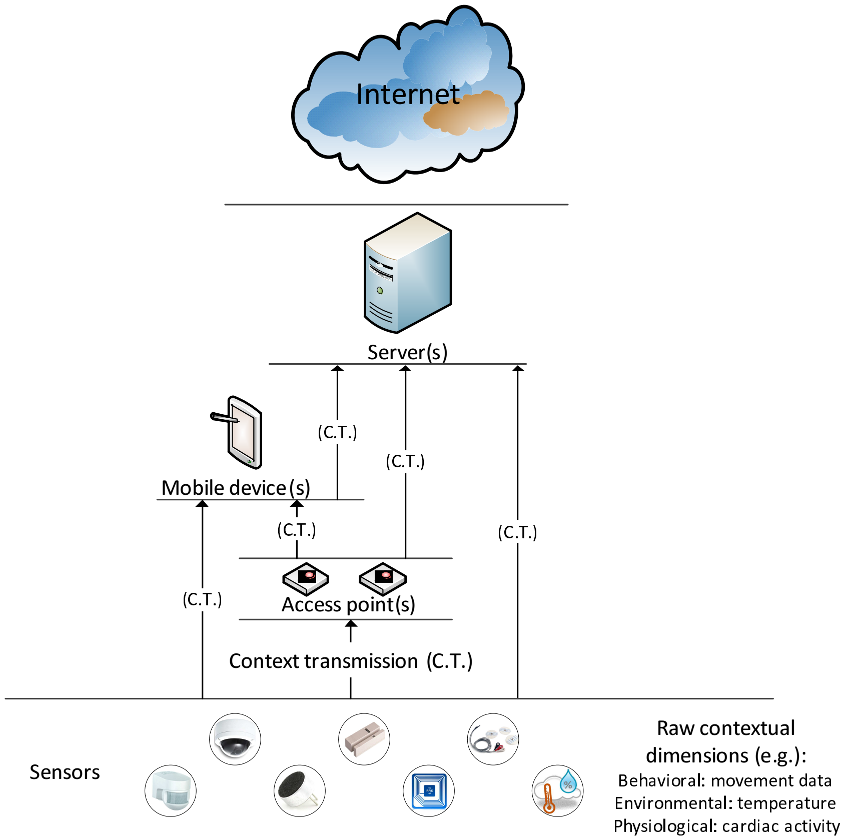


Figure 2.2 – General structure of a sensor network, layered structure identified based on devices' capabilities. HMS may have additional sub layers to comprises large sensing capacities.

the person, his behavior, the environment, performed activities, etc. Context-aware e-health systems need to have a full visibility of the person's context which requires using all the available sources. Data sources may be classified according to their used collection method (direct and indirect), event type (frequency mode), source type (physical or virtual) and sensor data (see Figure 2.3).

The collection of data can be categorized into two categories depending on how the system gathers data either directly or indirectly. Direct methods acquire data from hardware and sensors attached locally without intermediaries. The sensors capture the information constantly and, in most instances, relay these data wirelessly via numerous communication protocols to a home server or a coordinator. Indirect methods refer to data acquisition using a middleware-based infrastructure where the system becomes able to use sensor data thanks to additional software or hardware components. In this category, storage servers can be involved and data can come from databases, RSS (Really Simple Syndication) feeds, etc.

When referring to data collection, the frequency of receiving data plays an important role in the system performances. Data can be generated based on three event types: constant, interval and instant. Constant events ensure that data are continuously transmitted. For example, using an IP camera which sends continuously a video stream. In instant events, acquired data are instantly sent when a

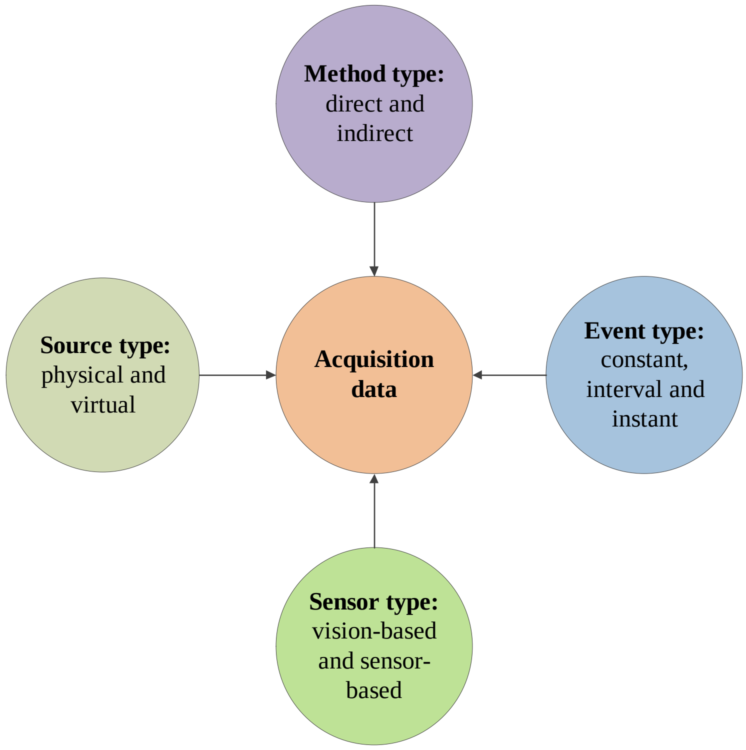


Figure 2.3 – Contextual data resources

certain event occurs. For example using a light switch or a door detection sensor. Interval events imply that the data are sent periodically following a uniform time interval. For example, sensing and sending the heart signs each 20 seconds with an ECG sensor.

In HMS, having full contextual information can be reached using all the available sources (physical and virtual) that can provide relevant context data. Physical sensors are the most common type of sensors used in HMS to generate and retrieve raw sensor data including the parameters of the person and his environment. Virtual sources refer to other data sources such as existing health records, historical data (e.g. the person's behavior and dependency level), the person's social media network, the profiles of persons involved in the overall e-health ecosystem such as patients, elderly, disabled and caregivers including professionals, nurses, volunteers, etc.

Sensor data have different formats: numerical, categorical, graphics, video, etc. Based on these formats and on the sensor types, the health monitoring can be classified into two categories: vision-based and sensor-based approaches. The vision-based approaches are based on a visual sensing such as video cameras for movement and gesture recognition while sensor-based approaches use a wide range of emerging sensors and technologies for health and biomedical monitoring.

Nowadays, systems and projects for healthcare monitoring rely on a set of common components and use standard and commercial sensors for the purpose of gathering raw data to monitor individuals and their environment. According to the research projects surveyed in this thesis, it is observed that there are three main classes of interconnected networks which are often used in this realm: Personal

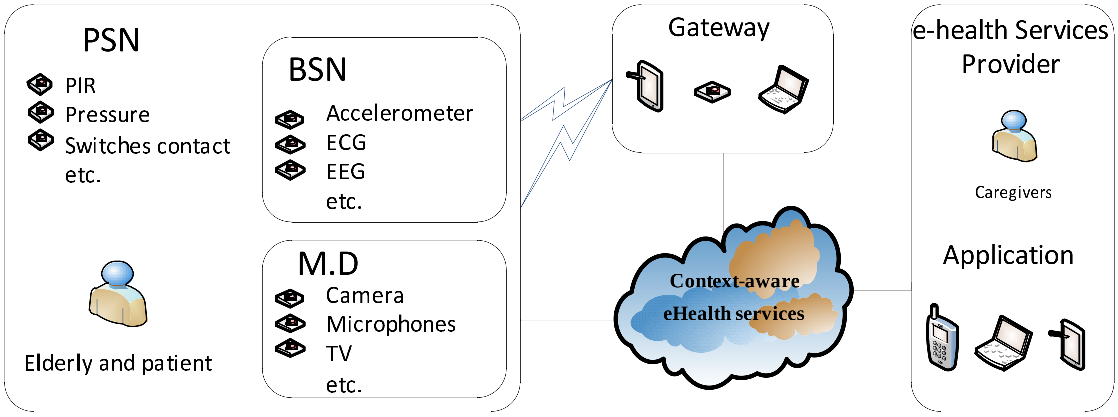


Figure 2.4 – Sensing scenarios in HMS

Sensor Network (PSN), Body Sensor Network (BSN) and Multimedia Devices (MD). Selected sensors and devices are integrated into the home objects and infrastructure and connected using the network technologies. Each sensor is responsible for one or more task at the same time.

Overall, PSNs are used to detect the human daily activities and measure the conditions of the person's environment. BSNs are used to monitor vital signs and health state by measuring physiological parameters and detecting ambulatory activities. Finally, more contextual information related to the human actions are collected via MD to monitor the movements, environmental changes and to increase the interaction between the monitored person and the e-health application. An overview of sensor networks in HMS is depicted in Figure 2.4 while Table 2.1 describes the three categories of networks and their purpose with the main sensors and devices used in HMS.

2.3.1.1 Personal Sensor Network (PSN)

The PSN or environmental sensors are responsible for capturing and retrieving the contextual data regarding the person and his environment. PSN can be emplaced in a living place or attached to different home objects in order to detect the person activities. Such objects can be a sofa, table, bed, chairs, or floors with pressure sensors. Personal interactions with household objects in a specific location combined with the environmental observations can indicate the person's performance of daily living activities (ADL). For instance, if a motion sensor identifies the current user location as *kitchen* and one sensor of cooking objects (e.g. gas, oven, toaster, or hob) is *On*, and there is a water usage or the refrigerator's door is open (using a mixer tap sensor or contact switches), then, sensed data definitely indicate that the ADL activity of *meal preparation* is taking place. Therefore, environmental sensors can provide rich contextual information to detect the daily activities and observe the human behavior in HSH [33].

Passive infrared (PIR) sensors are the most frequently used to detect the person's presence [34] and ADL [35]. The use of radio-frequency identification (RFID) includes active and passive tags attached to objects and readers worn by the person. RFID is used to identify users and objects of the HSH environment [36] [37].

Table 2.1 – Health Monitoring Devices and Sensors

Category	Name	Purpose	Data Format
PSN [1]	PIR	Motion detection	Categorical
	RFID	Persons and objects identification	Categorical
	Pressure	Identify location	Numerical
	Ultrasonic	Tracking location and posture	Numerical
	Contact switches	Open/close detection (e.g. doors)	Categorical
	Light	Use of light and its intensity	Time series
	Temperature	Measure room temperature	Time series
	Weight	Elderly weight	Numerical
	Humidity	Measure room humidity	Time series
	Power	On/off and measure power consumption	Numerical
BSN [2]	Accelerometer	Measure acceleration, fall detection, location and posture	Time series
	Gyroscopes	Measure orientation, motion detection	Time series
	GPS	Motion detection and location tracking	Categorical
	ECG	Monitor cardiac activity	Analog signal
	EEG	Measure of brain waves	Analog signal
	EOG	Monitor eye movement	Analog signal
	EMG	Monitor muscle activity	Analog signal
	PPG	Heart rate and blood velocity	Analog signal
	Pulse oximeter	Measure blood oxygen saturation	Analog signal
	Blood pressure	Measure blood pressure	Numerical
	SKT	Skin temperature	Numerical
M.D [3]	Cameras	Monitoring and tracking	Image, video
	Microphone	Voice detection	Audio
	Speakers	Alerts and instructions	Audio
	TV	Visual information	Audio, video

[1] Personal Sensor Network, [2] Body Sensor Network , [3] Multimedia Devices

Pressure [38] and ultrasonic [39] sensors can be attached to home objects to track their locations and therefore the movements of the user. Contact switches are used to detect the user's interactions with other objects in the space (e.g. door, window, fridge, etc.) to perform activities. Environmental sensors are used for additional dimensions such as light, temperature, humidity. They are deployed in different places to monitor the environment conditions and recognize the daily activities. Power sensors are used to measure and manage the energy consumption but also to detect the usage of electric devices using the On/Off events. The usage of electrical appliances such as microwave, water kettle, toaster, room heater and television can also be used to detect the activities and helps further to refine the knowledge of the behavior [40].

2.3.1.2 Body Sensor Network

BSNs use wearable sensors carried by the monitored persons such as elderly and patients. These sensors are used in HMS to provide a continuous flow of information and real-time health conditions. They are often embedded into accessories such as clothes, belts, watches, or glasses. BSN often use inertial measurement units such as accelerometers for detecting ambulatory activities or vital sign devices such as heart rate sensors for monitoring the health state. Accelerometers and gyroscopes are the most common inertial sensors used to monitor the movements and body postures such as standing, sitting, and walking. Accelerometer sensors measure the acceleration values typically based on three-axis accelerometers positioned on well-defined locations on the human body. The work in [41] used four accelerometers attached at the chest, left under-arm, waist and thigh to monitor and recognize five activities which are standing, sitting, lying, walking and transition.

In [42], a human activity recognition (HAR) method is proposed using four wearable accelerometers mounted on the left/right forearm and left/right shank of subjects. The proposed system monitored the performance of ten daily activities and gym exercises such as standing straight, sitting on a chair, walking, jogging, and weight lifting. Authors in [43] monitored twenty-six events and activities using a single accelerometer and gyroscope sensors to measure the orientation. Gyroscope sensors are typically used together with accelerometers for movement detection. In [44], accelerometer and gyroscope sensors were mounted on the right arm wrist and right foot of the person in order to collect linear accelerations and angular rates of motion and thus to recognize six activities which are walking, standing, writing, smoking, jacks, and jogging. Similarly, a fall detection system was proposed in [45] for elderly using accelerometers and gyroscopes. The global positioning system (GPS) can also be used as a wearable sensor to monitor location-based activities in an open or mobile environment. For instance to learn significant locations and predict the movement across multiple users [46] or to learn and infer the user's mode of transportation based on the data logs of GPS [47].

In HMS, several biosensors are used to monitor vital signs of patients and elderly such as heart rate, oxygen saturation, blood pressure, blood glucose, body temperature, weight, etc. We can cite the used wearable sensors embedded into watches [48] [49], shirts [50], and belts [49] [51]. Such sensors provide real-time physiological parameters and values related to the health condition of the monitored subject. There are various of biosensors used in HMS such as electrocardiography sensors (ECG) used to monitor the cardiac activity, electroencephalography sensors (EEG) used to monitor brain activity, electromyography sensors (EMG) used to monitor muscle activity, and electrooculography sensors (EOG) used to monitor the eye movements. Pulse oximeters are used to measure the oxygen level of the blood (i.e. oxygen saturation) while photoplethysmography sensors (EPG) are used to monitor the rate of the blood flow. Other biomedical parameters can also be evaluated such as using CO_2 gas sensors to evaluate gaseous carbon dioxide levels in order to monitor the respiration.

The majority of used devices do not offer an interface for a data relay. Indeed, most of the existing studies and projects were hardly trying to improve the mechanism of linking these devices to their infrastructure. The objective was to transform this category of sensors into context sources connected to the network and to be able to directly and automatically apply the data collection. Although there are several protocols and algorithms that have been proposed in wireless sensor networks, there

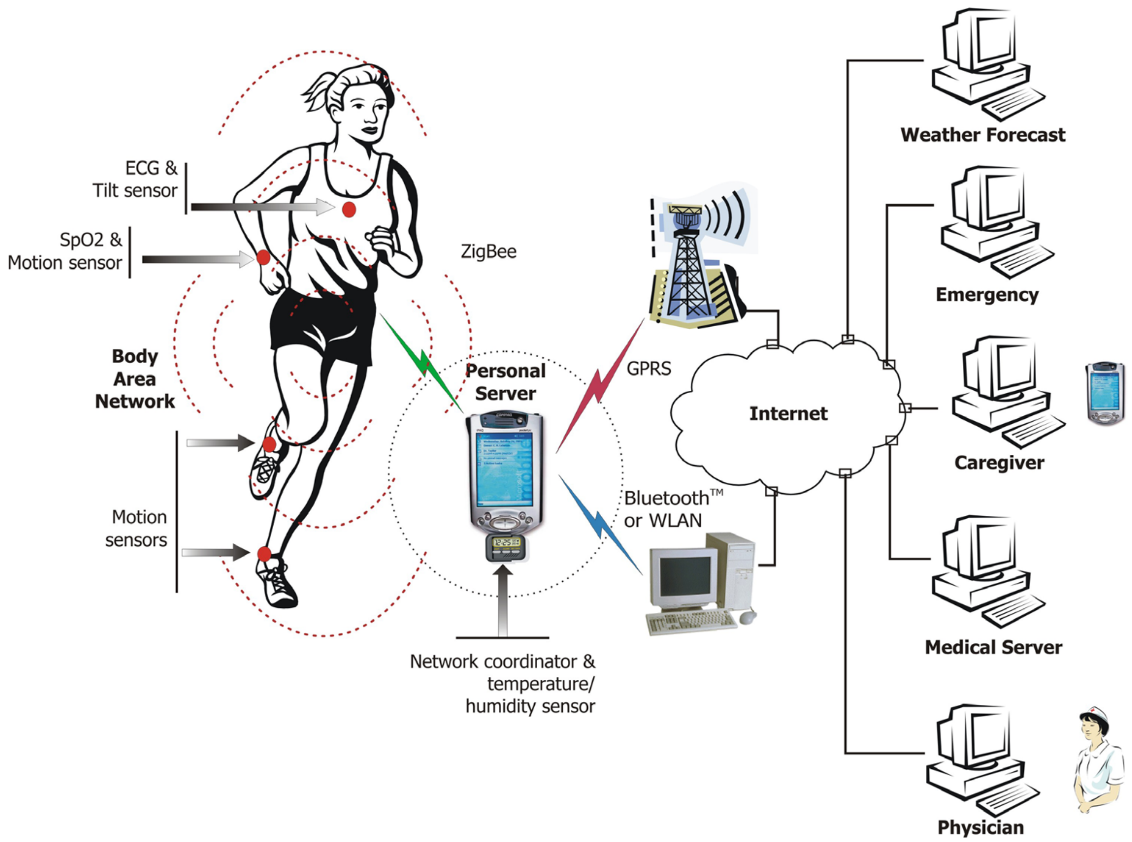


Figure 2.5 – The wireless body area network including intelligent sensors for the person's monitoring [2]

are no well-suited features and requirements for the body area networks (BANs) [52]. Parameters like the number of sensors, data rate, mobility, latency, communication, and transmission are selected based on the application type and the needs of the subject. In addition, the energy consumption and battery life are still one of the major challenges of devices used in such networks. The wireless body area network for patient monitoring, as presented in [2], is depicted in Figure 2.5.

2.3.1.3 Multimedia Devices (MD)

The widespread use of home appliances enriched by a set of sensors helps to create an interactive healthcare environment. Integrated appliances could be electric and electronic devices that offer several functions at home. Devices such as cameras, microphones, telephone, speakers and TV sets are able to establish a platform for the exchange of data between the resident and the system. These devices increase the resident interactions with health applications and represent either new sources to gather contextual information or portals used for guidance and counseling [53].

Multimedia-based approaches consider visual and audio sensing devices (e.g. cameras and microphones) in order to monitor the person. Sound-based detection methods can be used to monitor some activities of daily living [54][55]. Vision-based methods have a much wider scope and are used for postures recognition [56], human presence [57], movement and fall detection [58], and the monitoring of complex activities [59]. In spite of the used multimedia-based applications, there is disagreement in the adoption of such approaches. Although multimedia-based approaches provide rich contextual information, they suffer from computational costs and privacy issues.

Data acquisition varies from one sensor to another. The set of used heterogeneous sensors provides basic raw data which represent the low-level of the context. Low-level data are imperfect, uncertain by nature and less meaningful. Therefore, it is required for further development to build a high-level context abstraction that can be used in providing healthcare services.

2.3.2 Gateway and Communication Technology

A gateway is one of the key component used in HSH and HMS systems. Its main functionalities are the network interconnection, network management, and application management. A gateway is responsible for the coordination between heterogeneous sensors and connecting them to the Wide Area Network (WAN).

The ability of a gateway to perform data processing plays a major role in preventing the network congestion by reducing the amount of transferred data either directly or indirectly. The aim is also to take benefit from the software and hardware capabilities of the gateway in the design of advanced data analysis and processing. Intelligent algorithms can be used for data fusion and transmission control of data captured by heterogeneous sensors. For instance, by requesting a capture only when it is necessary for the purpose of a given service. Section 2.7 details numerous methods and proposed techniques based on the results of intelligent algorithms and reasoning approaches. A gateway can host local services and acts as a reactive system which faces some simple events such as temperature variation and smoke detection. More complex reactive and proactive services can be provided by analyzing the context of the resident and his environment in HSH. These services provide direct guidance to the resident and are able to send alert messages to caregivers. In most cases, the gateway is implemented through a fixed device such as a local home-box. However, the gateway can be a mobile device like a smartphone, a tablet, or a local smart sensor node placed in the environment or mounted to a computer server. In an overall scenario of a HMS, the gateway relays data using different networks such as fixed telephony networks, WiFi, cellular networks, and satellite networks. The available network technologies are combined to serve pervasive healthcare applications.

Sensor networks deployed in health smart environments are connected together to transfer and exchange data through different technologies and protocols such as ad-hoc networks and Internet. The Internet is adopted as an available solution for the remote communication that facilitates the access to data anytime and from anywhere. Integrated ad-hoc networks with different telecommunication technologies complement the sensing and communication infrastructure. Used sensors are combined and communicate either using wired or wireless protocols and technologies.

One of the commonly used protocols in the wired communication of HSH is the X10 protocol [60] [61]. X10 provides an easy way to transmits data over the already existing electrical wires of the home. It allows a remote control of devices plugged into the electrical power lines. X10 provides a small data rate (20 bit/s)

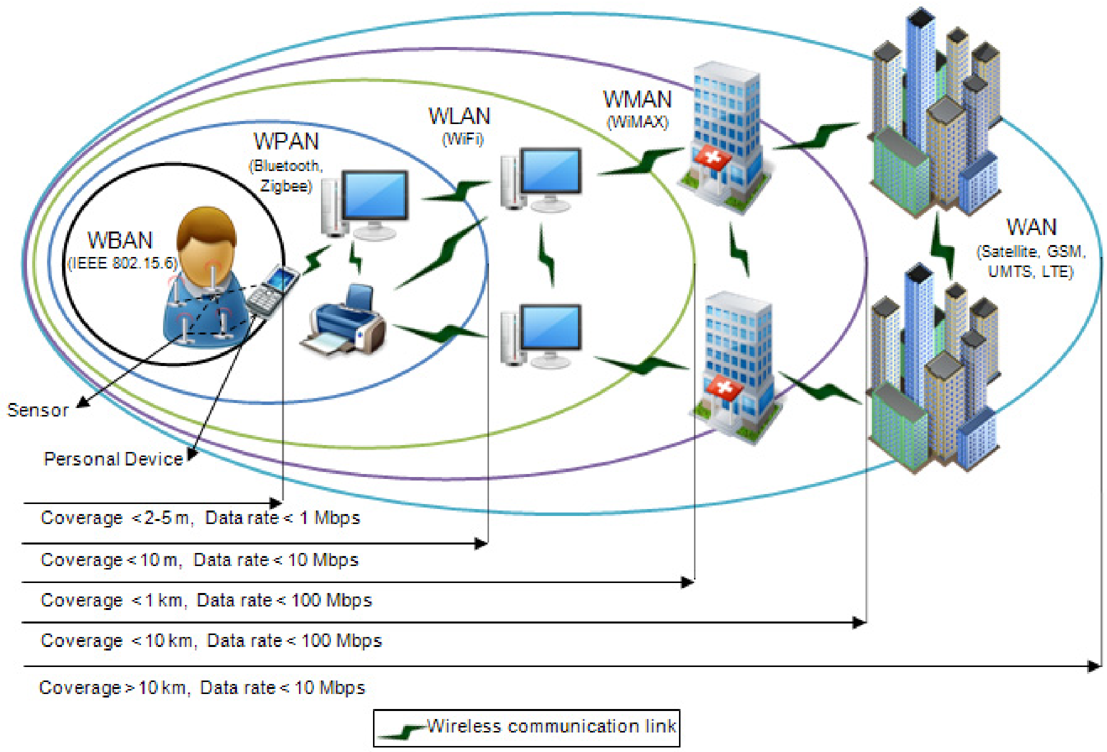


Figure 2.6 – Wireless technologies based on the geographical coverage [3]

and an unreliable connection mainly due to the electrical noise. Indeed, X10 devices may interpret an electronic interference as a reliable information or command and react accordingly. On the other hand, useful X10 data can be considered as noise in filtering [62].

Nowadays, various wireless communication technologies are employed to integrate health and medical applications with the network in order to improve the health services. Several wireless communication technologies are available to serve indoor and outdoor data transmissions among sensors, base stations or gateways in personal area and body area networks. The most popular and used technologies are the short-range wireless protocols such as Zigbee, Bluetooth, WiFi [63][64], and recently Bluetooth Low Energy [65]. Other wireless technologies are selected for specific applications such as the identification and tracking of persons and objects using RFID, IrDA, and UWB. These technologies are used together with large-scale wireless networks such as 3G/4G to provide advanced and pervasive health smart home applications and services. Figure 2.6 shows wireless networks that can be categorized based on their geographical coverage [3].

- Zigbee technology (IEEE 802.15.4): ZigBee is a specification for high-layer communication using protocols on top of the IEEE 802.15.4 standard. It is used for wireless personal area networks (WPANs) with a short-range radio communication. ZigBee was developed by the ZigBee Alliance for a cost-effective, energy-efficient and wirelessly networked monitoring. It is suitable for e-health applications that require low-cost, very low-power, and long battery life. This technology is simpler and less expensive than other WPANs like Bluetooth. ZigBee can operate with a data rates ranging from 20 Kbps to 250 Kbps. It supports three kinds of topologies which are mesh, star and cluster tree. Used devices can form a mesh network connecting several devices together and providing a multi-hop routing. There are three kinds of devices: the coordinator (the PAN coordinator), the router which is a full function device (FDD) and may act as a coordinator if needed, and the end device such as sensors and actuators.

- WiFi technology (IEEE 802.11): Wireless fidelity (WiFi) is a popular wireless communication and data transfer technology. It is based on the IEEE 802.11 series of standards used for wireless communications in a local area network (LAN). The high transmission speed is the main advantage of WiFi. The network supports star and point-to-point topologies where devices are interoperable with each other. The WiFi coverage can include several electronic devices able to connect to the local network or Internet through a wireless network access point (AP) with an average distance of 100 metres and broadband speeds up to 54 Mbps depending to the used IEEE standard. The disadvantage of this technology is relatively the large power consumption. WiFi represents a good candidate for sensors and devices which are deployed in HSH to ensure a continuous monitoring.

- Bluetooth technology (IEEE 802.15.1): Bluetooth (BT) is designed for short-range wireless communications. BT is an open wireless communication technology based on the IEEE 802.15.1 standard. It is used for connecting a variety of devices for data and voice transmissions in WPAN. The number of BT devices can be two or more up to eight in short-range network topology known as piconet. A piconet is a WPAN formed by a BT device serving as a master in the piconet while all the other synchronized devices are referred to as slaves.

- Bluetooth Low Energy technology (BLE): BLE is an emerging wireless local area network technology which provides ultra-low power consumption and cost and facilitates the interoperability among portable consumer devices. BLE devices are designed to be thin for power saving and cost supported with a battery life ranging from months to years [66]. BLE is selected as a low-power solution to control and monitor applications in areas such as healthcare and smart energy. It represents an efficient technology for transferring very short data packets and short connections with a minimal delay (latency) [65][67].

The selection and integration of communication technologies are still open issues and need to be addressed in the context of health smart home applications. Basically, energy consumption, reliability, interoperability, low cost, communication rate and distance are the main required aspects in the overall ecosystem for health monitoring, healthcare, and welfare services. Table 2.2 compares the features of various wireless communication technologies which are widely used in HSH.

Table 2.2 – Characteristics of some wireless technologies used in HSH

	Zigbee	**Wi-Fi**	**Bluetooth**	**Bluetooth LE**
Standard	IEEE 802.15.4	IEEE 802.11	IEEE 802.15.1	IEEE 802.15.1
Transmission frequency	868 Mhz, 915 Mhz, and 2.4 Ghz	2.4 and 5 Ghz	2.4 Ghz	2.4 Ghz
Topology	Mesh, star, and cluster tree	Star and point-to-point	Piconet	Piconet
Data rate	20, 40 and 250 Kbs	11 and 54 Mbs	1 to 3 Mbs	1 Mbs
Range (metre)	10 to 100	100	10	10
Power consumption	Very low	High	Medium	Very low
Cost	Low	High	Hight	Low
Battrey life	Months to years	Hours	Days	Months to years
Network nods	65000	32	8	Implementation dependent
Security	128-bit AES	SSID authentication	64-128 bit	128-bit AES
Optimized for	Low power and low cost, reliability, and scalability	Speed, flexibility	Convenience	Low cost and low power

2.3.3 End-user Application and Processing System

Providing context-aware services is the heart and most complex part of HSH. The two main actors who are directly involved in HSH applications are the monitored persons (e.g. patient, elderly, and disabled) and the healthcare provider (e.g. doctors, nurses, and volunteers within the network coverage). End-user applications mainly depend on the interaction between these two categories of actors. Provided functionalities are influenced by the user's context and available services. The processing system plays a major role in such context-aware applications where collected data must be relevant and then they are managed and interpreted. Required actions are triggered to provide proper and personalized services based on the context.

In general, context-aware applications have several features that have been categorized in several studies [68] [22] [23] [29]. In [68], Pascoe proposed a taxonomy of context-aware features which includes contextual sensing (detect and present the contextual information), contextual adaptation (the ability to automatically execute a service based on the context), contextual discovery (locate resources that are relevant to the user's context) and contextual augmentation (associate an annotation for the user's context together with the sensor raw data). Along the lines of the studies of [22] and [68], the authors in [23] identified three main features for a context-aware application which are the *presentation* of information and services, the automatic *execution* of services, and the *tagging* of information with the context. Authors in [29] clarified the usefulness of utilizing the contextual information for services or applications as a final step in context-aware systems. The presented context-aware features are *personalization*, to provide needed contents and information ; *suggestion*, to provide recommendations for the user's behavior; *configuration*, to automatically set up devices; and *user interface* to optimize and adapt the interface based on the user's context.

In general, the application has tow main parts: processing (reasoning) and acting. In the processing system, several reasoning approaches and machine learning algorithms are used to understand the person's context and determine the required services. More details about the reasoning approaches and machine learning algorithms will be presented in the following sections. The application implements a user interface, provides alerts and controls the sensors. The user interface is usually used to display parameters of the health status, vital signs, behavior changes, etc. Moreover, the application must perform the required actions commensurate with the user's context. That includes providing alert mechanisms in emergency situations (involving the message type, the network selection, the services provider, etc.) and/or instructions/recommendations for persons with special needs. Furthermore, the context-aware application motivates the sensor system based on the user's context. The objective is to provide an efficient monitoring that optimizes the system resources by controlling, for instance, sensing durations, frequencies, and data amounts.

In context-aware systems used in HSH, most of the features and requirements discussed previously are relevant along with others considerations such as scalability, reliability, privacy and security. The scalability of healthcare applications requires reasoning and inference functionalities. The work in [69] classified the issues of reliability in healthcare monitoring into three categories: reliable data measurement, reliable data communication, and reliable data analysis. Security and privacy are also of primary importance in the health monitoring because of the nature and the sensitivity of processed personal data [70] [71] [72]. Most of these issues will be discussed in depth in the challenges section.

2.4 Architecture of Context-Aware Health Systems

In order to achieve a pervasive healthcare system for independent living [73], a context-aware monitoring system should be able to observe, interpret and reason regarding the person's conditions including behavioral, physiological, and environmental information. In a smart home environment, the system should be able to perform actions and provide feedbacks to the person according to the results of the reasoning process.

Context-aware healthcare systems learn the human's normal behavior and understand the special conditions of the person and his environment. These systems help to identify unusual patterns of the daily activities and make accurate interpretations of the situation in order to make relevant decisions. Figure 2.7 shows the general structure of a context-aware health monitoring system. To provide the high-level applications with significant information, we identify three phases: data acquisition, processing, and analysis.

The architecture of health computing systems is defined by the types of system components and their interactive functions. This kind of architectures is strongly influenced by the computational capabilities of the used components (see Section 2.3 and Figure 2.2). As mentioned previously, the processing stage plays a major role ; it is used to identify the person's context and provide appropriate services accordingly. Note that most of the computational requirements of health monitoring systems are related to the achievement of the processing functionalities. Thus, the architecture of HSH is basically based on its processing system.

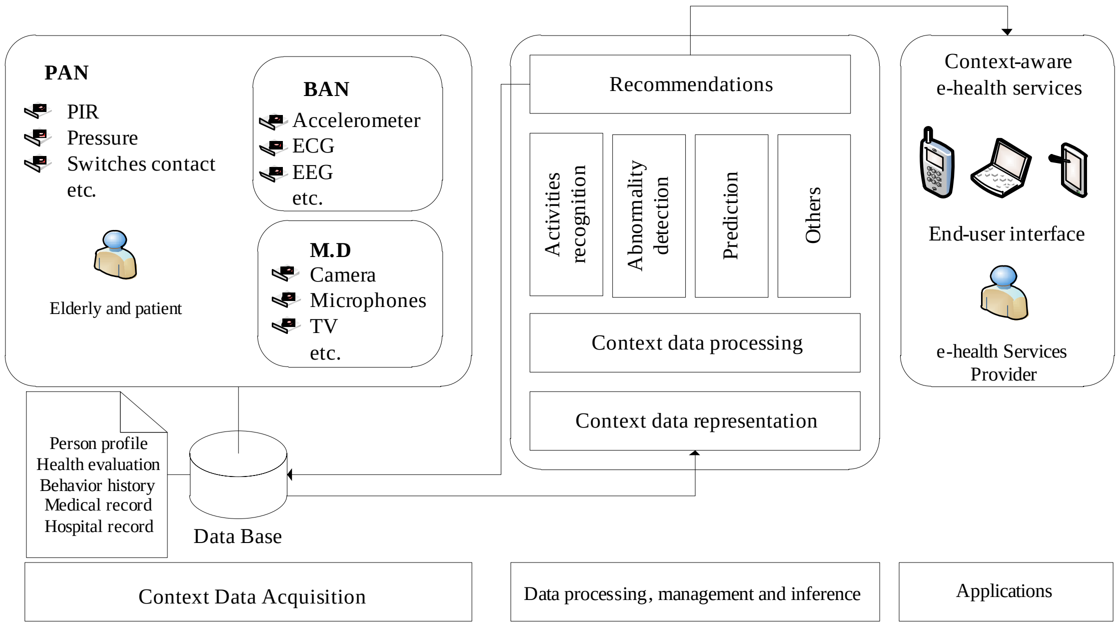


Figure 2.7 – Overall architecture of context-aware health monitoring systems in HSH

2.4.1 Architecture Style

Broadly, there are two main architectural styles of context-aware health systems in HSH: centralized architectures and distributed architectures.

Centralized architectures: in a centralized architecture, a central processing device (called centralized context server) is responsible for all the system functions. The main functions are the collection of data from sensors, data processing while executing various analysis with algorithms and reasoning techniques, providing services, and interfacing the local health system with the outside world.

The majority of existing health monitoring systems belong to the centralized architecture category [74][75]. The centralized context server must have an important computational power and be able to collect, process, and store data. In centralized architectures, communications are performed relatively easier than in distributed architecture. However, the drawback of such architectures is related to the failure tolerance when the central server crashes or when a network congestion occurs [75].

Distributed architectures: in distributed systems, each component works independently and manages its own context information. Each component communicates with each other over the network to transfer and share information. A distributed architecture benefits from the computational capability of each device belonging to the smart environment. Failed or less important components and devices can be ignored to continue the context-aware operations. The distributed system provides the opportunity to increase the reliability, availability, and performance of applications. The integration of existing system components, which are running on different platforms, are the most important feature of a distributed system. The important disadvantage of these systems lies in the complicated components design and maintain. Several potential failures could occur in the distribution system, mobile devices lack resources and computation power and local communications are usually faster than over the network which depends on the used communication technology.

Distributed architectures can use multi-agent systems (MAS) [76] or service oriented architecture (SOA) paradigms [77] to design and develop health monitoring applications. Mobile agents and multi-agent systems are used to improve the home care environment in which autonomous agents are used for different purposes and collaborate with each other by incorporating their knowledge. MAS is an option to design and establish a distributed intelligence and perform complex tasks. Multi-agent systems are used to solve the issues that could not be tackled using the centralized approach or using agents independently. Intelligent multi-agent systems are used to improve the healthcare and assistance to monitored persons. For instance, applications can provide a patient localization and management system [78], tracking locations and detecting abnormal behaviors along with a group-based collaboration [58], and providing a support for a comfortable, healthy and independent living [38][79].

Service oriented architecture is a model for reorganizing software applications and infrastructures into a set of interacting services. Service-oriented computing (SOC) is a paradigm which relies on SOA to use services as fundamental elements for developing applications [80]. Several health monitoring applications were developed based on SOA. A health service platform proposed for smart homes was presented in [81]. The platform integrates various devices and services and provides interoperability, modularity, and reusability of service components. Using SOA, some works provided an ambient assisted living [82][83] and integrated a vital sign monitoring and telemedicine platforms [84]. A framework of health services, including bio-medical monitoring, alerts, and communication with a coordination center was presented in [85]. The work of [86] presented a pervasive health system enabling self-management of chronic patients during their everyday activities.

2.4.2 Middleware

One of the main issues of e-health applications in HSH is heterogeneity. It is caused by the use of a variety of sensors and devices with different standards and modalities. Middleware represents a solution used to integrate several sensors and facilitate their interactions with the monitoring system. A middleware is defined as a layer between the networked operating system and the application. It represents a reusable solution for the issues related to heterogeneity, interoperability, security, and dependability [87]. Middleware plays a significant role in HMS to creates a common platform that helps to manage the complexity and heterogeneity of health sensor networks inherent in distributed systems. It provides an abstraction between software applications and the sensor hardware in order to simplify the application design. Several studies focused on the design and development of middleware solutions in health environments [27] [82] [88] [89], while some others focused on the challenges in developing such middleware [87] [90]. For example, authors in [90] identified the challenges in developing middleware solutions for sensor networks mainly in terms of abstraction support, data fusion, resource constraints, dynamic topology, application knowledge, adaptability, and scalability.

A cloud-oriented context-aware middleware for ambient assisted living (CoCaMAAL) was proposed in [82]. The system comprises five main cloud-oriented components: ambient assisted living (AAL) systems, context aggregator and providers (CAP) cloud, service providers cloud, context-aware middleware (CaM) cloud, and context data visualization cloud. The motivation of CoCaMAAL was that biomedical sensors lack the processing power to perform key monitoring operations, data aggregation, data transmission, and computation. The objective was to support body sensor networks in AAL. CoCaMAAL uses cloud computing to provide real-time services for assisted living. Basically, it is built upon SOA to perform the context modeling of raw data, context management, and service handling (mapping, distribution, and discovery). In [88], a context-aware middleware-based solution, called PEACH, integrates together various sensors in a Wireless Body Area Network (WBAN). The objective was to detect affective and physical conditions and to provide outdoor assistance using ad-hoc assistance teams comprising nearby volunteers. Similarly, in [91], a pervasive middleware, called AGAPE, was designed to assist ad-hoc groups of helpers in emergency situations for supporting elderly anytime and anywhere. The Context-Aware Middleware for Pervasive Elderly Homecare (CAMPH) [89], provides several system-level services including context operations (acquisition, storage, and reasoning) and service organization and discovery based on the context query processing. CAMPH was designed to facilitate the development and deployment of various homecare applications. The overall architecture consists of four logical layers: physical space layer, context data management layer, service management layer, and application layer. In [27] and [92], the authors designed a middleware to facilitate the development of a ubiquitous computing system for healthcare through autonomous agents in which agents can represent users, resources, or wrap complex system functionalities. Context Awareness for Internet of Things (CA4IOT) presented in [93], is a middleware architecture for IoT which has been developed to automate the task of selecting sensors according to the problems/tasks at hand. The middleware focuses on understanding the user requirements and selects the most suitable sensor able to provide relevant information to the users' context. The middleware architecture consists of four layers: sensor data acquisition layer, context and semantic discovery layer, processing and reasoning layer, data, semantics, and context dissemination layer.

Overall, in HSH, middlewares can be either proprietary and dedicated to a specific application or general based on open standards. According to our literature review, we observed that there is a dominant tendency to use open standards in the implementation of software and services for interfacing the HSH with the outside world. Most pertinent standards used to construct and develop middleware in HSH are Open Services Gateway initiative (OSGi) and Web services standards. In order to provide intelligent health services for subjects, there is a need to develop an integrated platform able to combine and manage several heterogeneous sensors and devices. The platform should provide a variety of health assistive services such as health monitoring, diagnosis, evaluations, and reminders. Furthermore, the platform should be flexible to add new application services and connect them with the outside world. We present, in the following, the OSGi and Web services standards.

- Open Service Gateway initiative (OSGi) is an open service-oriented framework that significantly simplifies software lifecycle management. It allows the implementation of a software solution as an independent service. Originally, OSGi was proposed for deploying services coming from different providers in order to be used as service gateways. OSGi is an open specification that integrates and manages various devices in a local network. It provides a dynamic discovery and collaboration of devices and services from different sources using standard interfaces.

In addition, the OSGi support of connectivity with the outside world promotes remote control and management. The peculiarity of OSGi is to provide a dynamic adjustment where the reusable software components, named bundles, can be manipulated (installed, updated, removed, etc.) independently of the device operations. In general, the OSGi framework can be adopted as a typical solution that allows managing and integrating different devices and hardware components in the network through a unified service-oriented approach. This property helps to fully comply with the need of a dynamic and reconfigurable approach for remote health monitoring [94].

- Web Services technology (WS) is a set of open standards and protocols which provide common methods ensuring the interactions and communication among applications, services, and devices running on disparate platforms. WS allows the access to software components through standard Web protocols. The W3C standards define a Web service as a software system designed to support interoperable machine-to-machine interaction over a network. WS provides standard means of interoperation between different software applications running on different and independent platforms and frameworks. The Extensible Markup Language (XML) is used to code/decode data and send/answer messages between clients and servers using the Simple Object Access Protocol (SOAP) conveyed by the Hyper-Text Transfer Protocol (HTTP). Web services can be easily accessed over the Internet thanks to the use of XML descriptions with three major standard technologies: SOAP, Web Services Description Language (WSDL) and Universal Description Discovery Integration (UDDI). Thus, WS allows to easily perform aggregation of descriptions, which can be accessed by several applications running on different environments. Hence, proposed systems can gain in interoperability and scalability for managing their heterogeneous systems and devices [95] [96] [97].

Several health monitoring systems were designed and developed based on the OSGi framework and Web Services. A wireless health monitoring system was proposed in [94] to measure, process, and transmit patient's physiological data to a centralized remote platform for data collection. Considered data cover the glucose in the blood, arterial saturation of oxygen, blood pressure, cardiac frequency, and weight. The system was built upon OSGi to manage the biomedical devices and define a service-oriented architecture. In this system, users can interact with TV by using a multimedia home platform (MHP) middleware to browse personal physiological data. The AAL framework presented in [98] provides a remote monitoring, emergency detection, activity logging and personal notifications dispatching services. The proposed service-oriented architecture is based on a heterogeneous sensor network composed of WSN nodes and personal mobile devices. The middleware is integrated into an OSGi framework that processes the collected data in order to provide context-aware services and enable a network control. In [99], a ubiquitous home healthcare environment architecture is presented. This architecture is composed of four main building blocks, which are the healthcare gateway (based on OSGi), the Zigbee portable medical devices, the remote management server, and the data center. Message formats were defined between the Zigbee coordinator and the Zigbee portable medical device. Devices are dynamically converted into UPnP devices. Since the software in the healthcare gateway was managed by OSGi, it can be remotely configured, managed, monitored, and diagnosed. Authors in [100] proposed an integrated OSGi-based service platform to aggregate diverse safety and health related services and provide personalized assistive support for elders. By leveraging the component-based architecture of OSGi service framework, the platform aimed to integrate heterogeneous devices, networks, data modalities to provide assistive services for elderly and promote the collaboration of devices and services with different sources.

In [101], a distributed and patient-oriented telehomecare system was developed based on Web services. The objective is to support a remote medical management with QoS, heterogeneous platforms and homecare across the global wide area networks. The system architecture includes five elements: environmental and home automation sensors, medical body sensors, a gateway, Web services technology and graphical user interfaces. The healthcare system proposed in [102] integrates OSGi with Message Oriented Middleware (MOM) and SOA. It provides a flexible telemedicine platform where the system was designed to ensure interoperability of applications and services over a variety of health networked devices. MOM was used to perform the system integration and reliable data transmissions. With the *publishing* and *subscription* abilities, new applications can be added without interfering with the other components of the system. Services were designed as Web services using XML and open standards. SOA was used as the key concept to define reusable components and service cooperation mechanisms in a loosely-coupled manner in order to create a healthcare server. A service oriented architecture for independent life and health support was proposed in [85] using OSGi and Web Service. The architecture provides services such as biomedical monitoring, alerts, and communication with a coordination center. The architecture was divided into three modules: a coordination center, a residential gateway, and a mobile gateway. The fixed gateway manages the home ambient intelligence, the mobile gateway handles the person ambient intelligence while the coordination center integrates both platforms. The coordination provided an extensible communication with the service providers.

2.5 Monitoring Functionalities

Context-aware HSH and assisted living systems for subjects, like elderly, aim to monitor and evaluate the person's health condition and his functional abilities regarding the achievement of daily activities [8]. Such systems are effective when they gain a good knowledge of the human's daily behavior. Indeed, the success of an intelligent HMS is measured by its ability to understand the normal behavior of subjects, detect the abnormal situations and predict future health conditions.

In reality, the human's behavior is highly dependent on perception, context, environment and prior knowledge [16]. Moreover, other significant factors can affect the human behavior such as the physical and mental state and changes like the perceptual abilities, physical skill, and memory. Therefore, a key challenge in a smart health system is to select the appropriate methods and techniques that can be effectively able to understand the complex and variable human behavior in performing the activities of daily living (ADL). A detailed explanation about the nature of daily activities (ADL, IADL etc.) and their specific characteristics will be discussed in Chapter 3. In this realm, several methods and researches were conducted for monitoring and assessing the functional abilities of subjects and their physiological and behavioral parameters.

Sensor data interpretation helps to provide a better understanding of the person's lifestyle in terms of performing the daily activities and detecting human behavior patterns which includes normal and abnormal status. Patterns are very useful in health monitoring system for supporting populations who suffer from age-related diseases such as cognitive decline and chronic diseases (diabetes, cardiovascular disease, Alzheimer's disease, etc.). The activities of these populations can be strongly influenced by their diseases. For instance, subjects with diabetes have different behaviors in performing activities such as frequent drinking, toileting, and sleeping. Therefore, the detection of changes related to the behavior patterns helps in identifying the subject's context, diagnosing illnesses, and providing appropriate services.

In this context, we identify three major functionalities offered by health monitoring systems: behaviour and activities recognition [43][44], abnormality detection [37][103] and behaviour and health prediction [104][105]. Many interesting reviews, targeting these functionalities, can be found in the literature. Most of these surveys have only focused on one aspect and ignored the importance of the rest of concepts. We can cite the vision-based activities recognition [106], sensor-based recognition [107], human activities recognition using wearable sensors [108], the analysis of complex activities and corresponding recognition techniques [109], anomaly detection in automated surveillance [110] [111], and the prediction of occupant behaviors [112]. We intend to present a comprehensive and consolidated picture of these functionalities including concepts, approaches, and processing techniques.

In health computing, all the desired functionalities are subject to monitoring approaches with the sensors used for capturing relevant contextual information. Processing and inferencing methods depend heavily on these types of used sensors. In this context, there are two main considered approaches which are the vision-based and sensor-based approach.

In **vision-based** approaches, monitoring the user's behavior and environmental changes is based on the use of visual sensing facilities such as video and audio streams. The generated sensor data from vision-based monitoring are video sequences or digitized visual data. The approaches exploit a set of computer vision techniques (vision-based reasoning) to analyze the visual observations for behavior tracking and pattern recognition. In **sensor-based** approaches, the monitoring is based on the use of emerging sensor technologies. The generated sensor data are often heterogeneous which are usually processed through several methods and technologies for detecting the human behavior (see sub-section 2.7). In these approaches, sensors can be either wearable sensors attached to an actor under observation with inertial measurement units (e.g. accelerometers sensor or ECG vital sign processing devices) or object-based sensors which are emplaced in the living place (see sub-section 2.3.1). Activities being monitored with wearable sensors are mainly related to ambulatory activities and physiological parameters while objects and environmental sensors mainly deal with ADL and IADL activities. All these sensors are used to gather the contextual and behavioural information of person.

Several studies and huge research effort were done in health monitoring using different sensing technologies and processing methods. The combination of technological advantages had stimulated considerable research on a global scale, which leads to several smart home projects that enhance the assisted living for subjects. For instance, CASAS [113], MavHome [114], GatorTech [115], SWEET-HOME [54], AILISA [116], Casattenta [117], CodeBlue [118].

2.5.1 Behaviour and Activities Recognition

Activities recognition is a well-known process in HMS which aims to monitor and analyze users behavior and their environmental conditions to infer the undergoing activities. The activity recognition is one of the most promising research topics for context-aware computing and ambient assisted living. The main goal of activity recognition is to detect or recognize the human activities and behavior patterns in real-life settings [119]. Thus, it becomes an essential element applied in many health applications such as the automation of human behavior monitoring for elderly people.

As mentioned previously, the human's behavior in performing the daily activities is complex and highly diverse. Thus, an accurate activity recognition is a challenging and complex task. The main challenges related to the nature of human activities were identified in [119] and are: (a) recognizing concurrent activities: performing several activities at the same time, (b) recognizing interleaved activities: activities that are overlapped with others in real life, (c) ambiguity of interpretation: similar actions may be interpreted differently based on the context, and (d) support of multiple residents: recognize the activities performed in parallel by the occupants in a group.

Many recent efforts have been made on human behavior recognition. In the literature, different approaches, methods, and algorithms were proposed and improved. Generally, the activity recognition field comprises many different topics such as activity modeling, behavior, environment monitoring, data processing and pattern recognition. Hence, in practice, the recognition of activities [108] can be roughly characterized by the following four basic tasks.

1. the use of appropriate sensors in the resident's environment to monitor and capture the behavior along with the environment changes

2. the collection and processing of perceived information through aggregation and fusion in order to extract high-level abstractions of the context

3. the design of computational activity models in a way that allows software systems and agents to conduct reasoning and manipulation

4. the design of methods and algorithms to efficiently infer activities from sensor data

2.5.2 Behaviour Abnormality Detection

Detecting the anomalies regarding the human behavior in performing daily activities and regarding the health conditions represents another challenging task. Anomaly detection, which is also known as outlier detection, is a widely studied topic that has been applied to many application domains. Generally, the definition of anomalies detection refers to finding a pattern in data that do not conform to the normal or expected behavior. The non-conforming patterns are often referred to as anomalies or outliers [120]. Anomaly detection is a complex process that requires learning the normal behavior patterns and then setting assumptions in order to distinguish between *normal* and *anomalous* in next observations. This process is heavily influenced by the methods applied to perform the detection, the choice of sensors and feature extraction. Authors in [111] have identified the general challenges facing the abnormality detection processes. In the following, we summarize the main challenges regarding the human behavior and health monitoring systems.

1. The definition of a region that represents all the possible normal behavior is difficult. Indeed, the boundary between a normal and an anomalous behavior is often not precise. Abnormalities located near to the boundaries can actually be considered as normal and vice versa

2. By its very nature, the human behavior patterns are irregular and are constantly changing. Thus, a present normal behavior may not appear similarly in the future

3. Anomalies are varying depending on the person's nature and the application domain. For instance, some behavioral and vital signs can be classified as anomalies with someone and not for others

4. Appropriate methods used in the detection of anomalies require training data with or without labeling which is usually a major issue

5. Data coming from sensors are often incomplete or contain noises which in some cases tends to be similar to real anomalies. This increases the process difficulty. Consequently, further prior processes are required for cleaning the data, filling missing values and removing outliers.

2.5.3 Behaviour and Health Prediction

As mentioned previously, sensor data interpretation leads to a better understanding of the person's context. The gained knowledge of the context is useful to evaluate the health condition of subjects based on their current state or in the detection of abnormalities in ongoing situations. In order to complete these functionalities, it is important to use long term situational data to predict future health conditions ahead of time and to make the necessary arrangements proactively.

Applying predictive methods represent another important task used in HMS to predict the evolution of the person's health state. This can be achieved based on the available historical data from the person's profile including health evaluations, behavioral history, medical and hospital records, etc. Applying prediction and analysis methods over these patterns helps to provide more related knowledge about the user's health trend and to gain the ability to notify caregivers if there is a high probability of health decline. Predictions are useful to automate the learning of the person's regular behavior which in turn can be used to detect irregularity or any deviation in the behavior compared to the regular norm.

2.6 Human Behaviour Representation and Context Data Modeling

During the acquisition data phase, the health contextual information is usually structured in multiple formats and different representations due to the heterogeneity of sensor records. A common modeling mechanism forms the basis to find readable and processable format. The context modeling concept referred also to the context representation of knowledge in a given system. The objective of modeling techniques is to define and represent data in a unified format in order to understand and share the knowledge in context-aware systems within the smart space community. There are several context modeling techniques used for data representation. In the current literature, the most popular methods used in health domain can be classified as key-value models, markup schemes, graphical, object-oriented, logic based, and ontology-based modeling. In the following, we briefly present the major methods used in health context representations.

Key-value modeling is the simplest used method for data representation. A list of *(key, value)* pairs is used to define the set of attributes and values. Authors in [22] used key-value pairs to model the context by describing the limited number of location information. Markup scheme modeling defines hierarchical data structures using a markup language such as XML. The markup tags (attributes and content of attributes) are used to represent and format the data. The work in [121] used the homeML schema to represent the resident's activities in smart homes. The use of the XML-based scheme was motivated by solving data heterogeneity and to represent, store and exchange data in a flexible way. Graphical modeling is a diagrammatic representation of contextual data at the design level. This modeling uses appropriate models such as the Unified Modelling Language (UML) used in [122] and Object-Role Modelling (ORM) used in [123]. Object-oriented modeling uses the concept of objects, with classes hierarchies and relationships, as a context modeling tool. It employs the encapsulation, reusability, and inheritance to represent context data. The work in [124] used a general object-oriented context model to propose a context-aware system in the smart environment. In this model, the context data is structured around a set of entities, each describes a physical or conceptual object such as a person or an activity. Contextual entities were linked to their attributes and other entities with defined relations.

In logic-based modeling, the context is represented as logical facts, expressions and rules. The logic-based knowledge representation models the sensor data and then exploits the logical rules to extract a contextual knowledge. In [125], a formal framework was proposed to represent the contextual sensor data in a smart home based on Description Logic (DL). Ontology-based modeling represents the knowledge and contextual information using semantic technologies. The main components of ontologies are concepts, instances, and relationships that can be used to form and represent the context. This modeling method emerged as the most interesting method used for data representation and reasoning [126] [127]. Authors in [128] presented an ontology-based context modeling and reasoning using the Ontology Web languages (OWL) to address the issues of formal context representation, knowledge sharing, and logic based context reasoning. In [129], OWL was used for ontological modeling and representation with a knowledge-driven approach for ADL. The approach establishes links between activities and contextual information through activity-based properties. We direct the reader of this thesis to [130] [127] [28] for further reading on context modelling techniques.

2.7 Learning Algorithms and Reasoning Approaches

Raw data, acquired from sensors, are worthless unless they are interpreted, analyzed and understood. Therefore, a key challenge in a smart system is to identify appropriate methods and algorithms that can effectively interpret the sensed data (low-level) and build new abstractions (high-level) in order to understand the complex and variable human behavior.

The task of context reasoning, also called inference, aims to deduce a new knowledge based on the available context data [131]. Context reasoning can be composed of three phases [132]: data pre-processing, data fusion, and context inference. Due to the nature of the sensors and network communications, sensed data may appear inaccurate or missing. The phase of pre-processing aims to make easier further processing by handling missing values, cleaning collected data and removing outliers. These tasks had their share of attention and research within the sensor network and data mining communities over the past years. In health applications, the full visibility of the person's context could not be reached using a single sensor. The data fusion is an extremely important task which aims at integrating data from multiple sources to produce a more complete and accurate vision in a reliable way. The context inference represents the most challenging task if compared to the preprocessing and data fusion. It aims to generate the real context of the subject based on the sensor data through several learning algorithms and reasoning mechanisms.

The range of methods and algorithms applied to detect the human context and behavior is extensive and varying in terms of several concepts. The adoption of these processing methods has a decisive impact on the accuracy of the final results. Thus, it is the foundation stone for the success of the whole system. In this subsection, we briefly introduce methods and techniques that have been widely used to recognize the human behaviors, detect the normal and abnormal situations and to predict future

Table 2.3 – Algorithms And Methods Used In Health Monitoring System

Functionalities	Methods categories	Algorithm and Techniques	Activity [1]	References
Behaviour Recognition	Statistical Techniques	Hidden Markov Model	ADL,AMA,PHA	[133][134][116][135]
		Bayesian Network	ADL, AMA	[136][137][138]
		Naıve Bayes	ADL	[139][140]
		Conditional Random Fields	ADL	[141][142]
		Multiclass Logistic Regression	AMA	[143]
	Computational Intelligence Techniques	Neural Networks	ADL,AMA	[144][145][146]
		Support Vector Machine	ADL,AMA	[147][42][43][44][45]
		Decision tree C4.5	ADL,AMA	[41][148]
		Clustering	ADL,AMA	[149][150]
	Knowledge-Driven	Rule-based	ADL,IADL	[151][38]
		Fuzzy logic	ADL,AMA	[56][152][153]
		Ontologies	ADL,AMA	[128][129][143][154]
Behaviour Abnormality Detection	Statistical Techniques	Gaussian Mixture Model	ADL, AMA	[58][155]
		Hidden Markov Model	ADL,AMA	[105][156][157]
	Computational Intelligence Techniques	Neural Networks	ADL,AMA,PHA	[158][159][160]
		Support Vector Machine	ADL,AMA	[161][162]
		Clustering	ADL,AMA	[37][163]
	Knowledge-Driven	Fuzzy logic	ADL	[164][165]
		Ontologies	PHA	[166]
Prediction	Statistical Techniques	Hidden Markov Models	ADL, AMA	[167][168][169]
	Computational Intelligence Techniques	Neural Networks	ADL,AMA	[170][171]
		Support Vector Machine	ADL	[172]
		Data Mining Techniques	ADL,PHA	[173][174][175]
	Knowledge-Driven	Fuzzy logic	PHA	[176][177]

[1] Activity of Daily Living (ADL), Instrumental Activity of Daily Living(IADL), Ambulatory Activity (AMA), Mental Functions (MF), Physiological activities (PHA), more details see next Chapter 3.

health conditions. We broadly classify techniques into three categories: probabilistic and statistical techniques, computational intelligence techniques, and knowledge-driven techniques. Table 2.3 demonstrates the uses of these methods and techniques.

2.7.1 Statistical Techniques

Statistical techniques are the most commonly used techniques for modeling the human behavior in the healthcare field. They have been used to deal with all the operations related to the behavior recognition, detection, and prediction. Broadly, these methods were used to find the dependence and correlations between the temporal information captured by sensors and the estimated person's behavior. Methods like hidden Markovian models (HMM) and Bayesian networks are probabilistic reasoning concepts derived from statistical inference processes [178][16]. Probabilistic methods were commonly used for modeling the behavior due to their ability to present random variables, dependence and temporal variation between collected data [16]. In the following subsection, some statistical techniques commonly used are reviewed.

2.7.1.1 Hidden Markov Model

HMM is a statistical technique where the system uses a Markov process with hidden (unknown) parameters. It defines a number of hidden states and observations used to model a given behavior. The hidden states represent the activities and the sensor data represent the observable output. A HMM is defined by matrices which encode the possible states and probabilities of observations. State transition matrices describe the likelihood of the process moving into a new state.

The HMM and its extensions such as the Couple Hidden Markov Model (CHMM) [133], Hierarchical Hidden Markov Model HHMM [134][167], Hierarchical Context Hidden Markov Model (HCHMM) [156], and Hidden Semi-Markov Model (S-HSMM) [157] were used for several processes including the recognition of daily activities [116] [133] [179], abnormalities detection [105] [156] [157], and behavior prediction [167] [168] [169]. The main drawback in basic HMM is the lack of hierarchy in representing the human behavior [16]. This problem can be solved using the Hierarchical Hidden Markov Model (HHMM) [134] [167] [60]. HMM has the difficulties experienced in processing large low-level sensory data (i.e. temporal data coming from different time scales) [180]. Moreover, using HMMs as a time series prediction model needs a large and growing number of time sequences.

2.7.1.2 Conditional Random Fields

Conditional random fields (CRF) is another statistical modeling method often applied in pattern recognition. It is different than the HMM model which assumes that all the observations are independent and thus it could possibly miss the complex relationships between observations. Indeed, CRF is an alternative probabilistic model which do not make independence assumptions between the observations and represents conditional probabilities of sequential data. CRF has been compared to HMM for activity recognition and detecting patterns in [141]. Generally, the authors found that CRF provides better classification and accuracy than HMM. However, CRF requires more computation of training data, especially if a large number of features are concerned.

2.7.1.3 Bayesian Network

Bayesian networks are statistical tools that provide a more general framework for modeling the human behavior. The key problem of Bayesian networks is that the exact probabilistic inference is intractable [181]. There are several examples of using Bayesian networks for behavior modeling such as in the monitoring and detection of human activities [136] [137] [138]. Naïve Bayes classifier (NBC) represent simplest possible probabilistic classifiers which are based on Bayes' theorem in order to perform Bayesian inference. It has been used with promising results for activity recognition in [139] [140]. However, the NB classifier needs large amounts of data to provide a good accuracy of recognition. Moreover, it does not explicitly model any temporal information, which is usually considered important for the activity recognition in a smart space.

Unlike the study in [141], a systematic study has been conducted in [142] in order to compare the performance of three activity recognition models: NBC, HMM, and CRF model. They evaluated these models using the dataset combined from the CASAS smart home project to recognize eleven activities of daily living. The activities are personal hygiene, sleeping, bed-to-toilet, eating, cooking, working, leaving the home, entering the home, relaxing, taking medicined, and bathing. These activities were analyzed using sensor event datasets collected from seven physical testbeds. The result of the recognition accuracy using 3-fold cross-validation over the dataset is 74.87%, 75.05%, and 72.16% for NBC, HMM, and CRF respectively.

2.7.1.4 Gaussian Mixture Model

Gaussian Mixture Model (GMM) is another probabilistic model that was investigated in the literature to learn the normal behavior in performing ADL activities and detecting abnormalities in a smart space. GMM was used along with a rule-based reasoning in [155] and with a vision-based reasoning in [58] in order to learn the normal behavior and detect abnormal situations.

2.7.2 Computational Intelligence Techniques

Computational intelligence techniques were widely used in the literature as an alternative to the statistical methods. These techniques, such as neural networks, support vector machines (SVM), data mining, decision tree and fuzzy systems, were used to recognize activities, distinguish between normal and abnormal behavior patterns, and predict the human behavior and health conditions.

2.7.2.1 Neural Networks

Artificial Neural Networks (ANNs) have been widely used in the field of intelligent computing. They represent a mathematical tool in artificial intelligence field that provides robust self-learning ability on data classifications. ANNs have been employed in pervasive healthcare monitoring systems. An ANNs-based structural health monitoring scheme with wireless sensor networks was proposed in [182]. The simulation results show higher accuracy in data processing with NN compared to other classification algorithms including Support Vector Machine, Decision Tree, and Logistic Regression. ANNs were also used to detect abnormal patterns in vital signs with BSN [160], provide individualized embedded diagnosis and decision support for remote health monitoring [183], and recognize ambulation activities along with transitions among the activities [144]. A temporal ANN-based embedded agent was proposed in [146]. The agent is able to work on real-time data from unobtrusive low-level sensors and actuators. The work recognized behavioral patterns of ADL activities and used these patterns to detect abnormalities in the temporal order in which activities take place. The predictive modeling engine, proposed in [171], applied a mining of the ADL data using machine learning algorithms with ANN.

Different combinations of ANNs were used for learning the daily routine activities of subjects in the smart environments. Multi-layer perceptron (MLP) neural networks were used with a single hidden layer to identify the human motions [158]. The authors in [170] used MLP as the prediction technique to anticipate the person's next movement. The authors in [184] have applied different learning algorithms to recognize the age categories and to detect possible changes in the individual's health condition based on walking data patterns. The used algorithms were MLP, decision tree, support vector classifier, Naive Bayes and Bayesnet. In their experimental results, MLP gave the highest accuracy in classifying the categories. The work in [145] proposed a self-organizing map to detect and recognize the activities of daily living. The proposed system was based on a self-adaptive neural network algorithm called Growing Self-Organizing Maps (GSOM). A one-pass neural network system used to detect the person's activity was discussed in [159]. The authors have introduced a new layer that helps for differentiating normal and abnormal behaviors based on the frequencies of ADL.

2.7.2.2 Support Vector Machines

Supervised learning techniques such as Support Vector Machines (SVMs) were widely used for pattern recognition and classification. For instance, for ambulatory activities recognition and fall detection [161] [44], ADL recognition and classification [147] and learning situations [103]. In [185], SVM was used with HMM to detect the abnormalities within an elderly behavior pattern where HMM was applied to train the normal ADLs and then, SVM was used to classify the normal and abnormal behavior. Authors in [172] applied SVM classifier to build a behavior classification model and learn the user habits related to ADL for predicting and identifying the behavior. The process enabled the prediction of home daily activities such as grooming, eating, sleeping, and having breakfast. However, the results were limited to a reduced set of activities which were achieved only in the early morning.

2.7.2.3 Data Mining and Machine Learning Techniques

Different data mining and machine learning techniques, such as clustering and decision tree, were used to classify data collected from sensors and to detect and predict the human behavior. Data mining and discovery of knowledge in large historical databases can be useful to extract hidden information during the health monitoring [186]. Decision tree builds a hierarchical model in which each branch from nodes to edges is a classification rule and represents a possible decision. The C4.5 algorithm is the most widely used decision tree classifier in activities recognition. In [148], five accelerometers were attached to hip, wrist, arm, ankle, and thigh in order to recognize twenty ADL and ambulatory activities (AMA). Four different classifier structures were used of which decision tree with C4.5 provided the best accuracy. Similarily, the work in [41] evaluated the effect of multiple sensors on the human body to evaluate the recognition accuracy. The authors investigated five classifiers (ANN, Decision tree, K-Nearest Neighbour, Naïve Bayes and SVM) to recognize five ambulatory activities using four sensors. It was also stated that the decision tree classifier was the best algorithm. Moreover, the authors explained that ANN, K-Nearest Neighbour, and SVM classifiers were computational expensive although they provide good performance.

2.7.2.4 Clustering

Clustering methods such as K-means, Fuzzy C-means (FCM), Self-Organising Maps and K-Nearest Neighbour (KNN) are unsupervised techniques that can be used for modeling the human behavior, the recognition of activities and the detection of abnormality. The clustering process follows a simple and easy way to classify a training data into a certain number of clusters and then use the clusters to classify testing or observed data. A human posture recognition system for video surveillance was proposed in [150] using one static camera. Training and testing stages were implemented using four different classifiers which are K-Means, Fuzzy C-Means, Multi-layer perceptron Self-Organizing Maps, and Feedforward Neural networks. The experimental results indicated that the Self-Organizing Maps shows the highest recognition rate.

In [175], different data mining techniques were compared to classify and predict health data of residents in a smart home. These studied techniques were KNN, SVM, MLP and Lazy Locally-Weighted Learning (LWL). The study showed that KNN outperformed other classifiers for the classification and prediction of health status. The FCM clustering technique was used in [163] to identify the normal behavior. The used data were related to the movement and location of elderly at home. Thresholds were set to identify the abnormal behavior following the detection of data points outside the clusters. Author in [174] classified patients with heart failure using a K-mean clustering. The clustering of patients was based on contextual information, like medical conditions and socioeconomic status, used in predicting the health status. In [37], the abnormal situations like falls and faints of elderly were also identified using K-means clustering. The study in [173] achieved a comparison of three indoor positioning techniques based on location fingerprinting. The comparison was achieved using K-Nearest-Neighbor, probabilistic methods and neural networks and reveals that KNN reports the best overall performance for the indoor positioning purpose.

The selection of one of the previously discussed techniques for modeling the human behavior depends primarily on the accuracy of its results. According to our survey, several factors definitely affect the accuracy of the results and show a disparity between reviewed studies and projects. Factors are mainly related to the type and amount of data used along with the type and number of sensors, placement of sensors, and the type and number of activities. Selected algorithms and methods may need to process a huge amount of data to learn and detect the human's behavior and the user's context. Therefore, such methods can provide a good performance but with high computational cost [187].

2.7.3 Knowledge-Driven Techniques

Knowledge-driven techniques are another approach used for modeling the human behavior. It is motivated by the observations of the real world where most of the human's activities are routines and usually take a similar the sequence of actions. In particular, these routines took place in a relatively specific circumstance related to the activity concept including time, place, frequency, objects, etc.

In this method, activity models involve the exploitation of a rich prior knowledge to develop a formal logical reasoning and deduce the human behavior. Developed models are generally used for activity recognition, abnormality detection and behavior prediction. Knowledge-driven techniques need to apply all the available knowledge of the problem domain to generate models and rules that can be used for inferring high-level abstractions of the context. The success of such approach heavily relies upon the accuracy and completeness of the prior knowledge. Here, the most popular used techniques in this approach are Rule-Based, Case-Based, Fuzzy logic, and Ontology-Based Reasoning.

2.7.3.1 Rule-Based and Case-Based Reasoning

Rule-based methods are the simplest reasoning techniques in which the human behavior is modeled using a set of primitive rules. These rules enable building a descriptive model for the human behavior detection. This technique can be used to generate a high-level abstraction using the low-level context. However, the complex human behavior can not merely be detected directly from rule-based approaches. The rule-based reasoning was used in [38], and combined with Bayesian networks in [151] for the activity recognition and behavior detection. In the Case-based reasoning (CBR) approach, the context knowledge is deduced from previous successful solutions to similar problems (i.e. the basis of previous similar cases). Case-based reasoning has also been used in the human behavior and activities recognition, such as in [188] [189].

2.7.3.2 Fuzzy Logic Reasoning

Fuzzy systems were used to manage and model the data uncertainty in sensor networks. A fuzzy learning and adaptation approach, called adaptive online fuzzy inference system (AOFIS), was proposed in [190] in order to model the resident's behavior by extracting the fuzzy membership functions and learning the fuzzy rules. The fuzzy logic applied in [153] was integrated into a recognition system for the activities of daily living for elderly. The authors in [152] used fuzzy membership functions for the movement detection and estimation of the activities of daily living. The authors found that the estimation is very hard in the living room using this approach. Therefore they focused only on a limited set of three activities, which do not meet the full requirements of a complete remote monitoring. Authors in [176] have presented a comparative study using a fuzzy expert system and neuro-fuzzy system (NFS) for heart disease diagnosis. They explained that NFS is the more appropriate model to measure the risk factor than the fuzzy expert system. Fuzzy set theory is usually used in the control of automated systems in complementarity with other techniques such as rules-based [165] or ontology rules [181] in order to optimize the context reasoning. The system called Context-Aware Real-time Assistant (CARA) [165] presented a context-aware hybrid reasoning framework that integrates fuzzy rule-based reasoning with the case-based reasoning for a pervasive healthcare. The framework was designed for home automation, continuous health monitoring and the prediction of possible risky situations. However, in spite of the context-aware reasoning, the results have been confined to limited activities in order to evaluate the system's effectiveness and efficiency in assessing the elderly conditions.

2.7.3.3 Ontology-Based Reasoning

The ontology-based reasoning methods are the most widely used techniques to build context-aware systems in the healthcare domain. According to [191], the ontology is a suitable model and method for the context representation and reasoning. It allows sharing the knowledge in a dynamic environment, enables an efficient context reasoning and guarantees the interoperability in pervasive computing systems. Ontologies are based on a description logic and knowledge representations. Mainly, the ontology reasoning technology is supported by two common representations of semantic Web languages: Resource Description Framework (RDF) and Web Ontology Language (OWL). For the health monitoring, reasoning and decision-making systems based on ontologies have been proposed in several studies such as in building context-aware services in e-health systems [192] and real-time remote monitoring using the patient's diagnosed with congestive heart failure (CHF) [166] . An ontological reasoning combined with statistical inference (multi-class logistic regression) was presented in [143] for the activities recognition. Authors in [154] introduced the context-aware infrastructure ontology to improve the recognition system in a smart home domain. This study addressed three goals. First, the design of a context-aware ontology to model the context which includes home sensors, human locations, times, and human postures. Second, object-based and location-based concepts were presented to distinguish the different activities. They used Description logic (DL) rules for making the human activity decision. Third, an ontology based activity recognition system (OBAR) was developed based on the two previous goals. The outputs of OBAR show the recognized activity based on user's context. The work targeted thirteen activities which are sitting & relaxing, sitting on the toilet, watching TV, working on a computer, eating or drinking, sleeping, lying down & relaxing, wash the dish, take a bath, make a drink, cooking, sweep the floor and scrub the floor.

Authors in [193] presented a system (called RADL) for recognizing the activities of daily living in order to detect and monitor ADLs for elderly in smart homes. The proposed ontology supports the semantic discovery of location, devices, and the environment of smart homes. The reasoning process discovers the activities and the appropriate service for the present situation. Similarly, a knowledge-driven approach for activity recognition using multiple data streams was proposed in [129]. The proposed system was based on ontological modeling and semantic reasoning for activity modeling and recognition.

In spite of the proposition of several ontologies used to optimize the monitoring, there was no uniform standard that meets all requirements of a context-awareness e-health system. In addition, the ontology based reasoning is unable to find missing values or ambiguous information compared with other methods. The approaches studied in this section, are the most popular learning methods and reasoning techniques that have been used for detecting the human behavior and extracting the context in health smart environments. It is clear that each method has its strengths and weakness. Comparing the performance of these techniques in an experimental research within a limited scope could not truly reflect the effectiveness of the overall health monitoring system. There is no single technique that can be used to address the different facets and complexity of a context-aware HMS. Therefore, what emerged from the previous review is that the best approach is to combine multiple methods which complement each other and provide a comprehensive picture of the person's context in a smart space [105] [194]. One trend in this direction is the context-aware model for changes detection, using machine learning and statistical methods such as the model proposed in [105]. The model used an HMM-based approach for detecting anomalies in a sequence of daily activities. In addition, a statistical process has been used to identify the irregularity in routine behaviors (i.e. shift in daily routines) and a simple exponential smoothing (using the Holt's liner trend method) was used to predict and detect changes in vital signs. The outputs of these processes were combined to fuzzy rule-based model to make the final decision. However, the main problem with such proposed system is the required high computational cost. Using huge amount of computed data with HMM and fuzzy rule-based for detecting the abnormalities (in terms of sequences of daily activities) may be an ineffective regarding to mood swings in performing the different activities.

2.8 Health Monitoring Systems and Healthcare Applications

In the past decades, many systems and applications have been developed for monitoring the elderly and patients in smart environments. There is no a single way to classify these applications which generally aim to identify the subject's context and provide proper services. These applications share the objective of enhancing the subject's quality of life, health status and compensate the cognitive decline.

According to our literature review, it is observed that there are three main categories of such systems which are ambient assisted living (AAL), movement tracking and fall detection (MTFD), and physiological health monitoring (PHM). In the ambient assisted living category, the application monitors and evaluates a list of basic daily activities, such as eating and washing, and allows the subject to live independently. The application provides the person with accurate services involving caregivers. Movement tracking and fall detection systems are ambulatory activities detection including dynamic activities, static postures, location tracking and accidental falls systems. Physiological health monitoring systems use real-time applications with the purpose of monitoring and diagnosis the vital signs for dependent and chronically ill persons such those suffering from diabetes, hypertension and cardiovascular related diseases.

In this realm, prototypes are varying in many aspects including hardware materials, software architectures, processing systems, functionalities, and services. In this section, we discuss these applications within the previous categories (i.e. AAL, MTFD, and PHM). We summarize and evaluate the most significant works found in the literature for each category. The qualitative evaluation encompasses the following aspects.

- Category and purpose: Ambient Assisted Living (AAL), Movement Tracing and Fall Detection (MTFD), and Physiological Health Monitoring (PHM)

- Functions: resignation (R), anomalies detection (A), and prediction (P) (see section 2.5
- Services: main provided services
- Activities: Activity of Daily Living (ADL), Instrumental Activity of Daily Living(IADL), Ambulatory Activity (AMA), Mental Functions (MF), and Physiological activities (PHA), (more details are in Chapter 3)
- Processing system: methods and algorithms used to manage, interpret and analysis data (see section 2.7)
- Context-awareness: among the health monitoring applications there are different context-aware considerations. Some works provide rich context information about the subject's status while others were confined to some limited information. This variety leads to different levels of contextual information (low, medium, and high)
- System architecture: mainly centralized (C) or distributed (D) (section 2.4)
- Sensing: the type and number of sensors (single or multiple). The size of the sensor network and the way in which sensors are used (e.g. carried by the subject or installed in specific areas) could increase the level of inconvenience (section 2.3.1)
- Intrusiveness: the system's degree of intrusiveness
- Communications: the different communications technologies used according to the sensor type and the application area (section 2.3.2)
- Gateway: the architecture component which receives data, controls the environment and communicates with caregivers and the outside. This component can be defined using a fixed LAN home server, a mobile device using the cellular network (e.g. using a smartphone or tablet), or both of them (see section 2.3.2)

In the following subsections, some applications are detailed while the important features are given for others. Table 2.4 lists a subset of the applications surveyed in this study.

2.8.1 Ambient Assisted Living

The progressive decline in physical and cognitive skills of subjects, in particular the elderly, coupled with common diseases (like Alzheimer's, dementia, and diabetes) prevent persons to independently perform their basic activities of daily living such as eating, hearing, dressing, and washing. The human behavior in performing these activities can be significantly influenced by the mentioned diseases. For instance, the impact on activities due to diabetes with frequent drinking, toileting, and sleeping. Therefore, there is a real need to develop monitoring and assisting

Table 2.4 – Overview of Health Monitoring Applications in HMS

	Project	**Functions**	**Services**	**Activities**	**Methods**	**Context-awareness**	**Architecture**	**Sensing**	**Sensing Type**	**Intrusiveness**	**Communication**	**Gateway**
AAL[1]	Auto-Dep [8]	A	Dependency Evaluation	ADL, IADl, AMA, FM (#8)	AGGIR-based Algorithm	High	D	Multi	PAN, BAN, MD	Low	Bluetooth, Wi-Fi, Zigbee	H. Server, Mob. Device
	CASIS [38]	A	Reminder	IADL (#2)	Rule-based Reasoning	Medium	D	Multi	PAN, BAN, MD	Medium	N/A	H. Server, Mob. Device
	AICO [195]	R	Location-based Recognition	ADL, AMA (#11)	Bayesian Network	High	S	Multi	PAN, MD	Low	IEEE 802.15.4	H. Server, Mob. Device
	BADL Estimation [152]	R	ADL Estimation	ADL (#11)	Fuzzy rules	Medium	S	Single	BAN	Medium	Zigbee	Home Server
	CARA [165]	A, P	Personalized Healthcare Services	ADL (#3)	Case-based and Fuzzy Rule-based Reasoning	High	S	Multi	PAN, BAN, MD	Medium	Bluetooth	H. Server, Mob. Device
	Wellness [196][104]	R, P	Wellness Determination	ADL, IADL (#6)	Statistical Functions	Low	S	Multi	PAN	Low	Zigbee	Home Server
	N/A [197]	R	Low-cost and Energy, Acceptance	ADL, IADL (#9)	SVM	Low	S	Multi	BAN	Low	USB, RF	Home Server
MTFD [2]	ANGELAH [58]	A	Fall Detection, Closest Emergency Volunteers	AMA (#1)	Vision-based Reasoning, Gaussian Mixture	High	D	Multi	PAN, MD	Medium	Wi-Fi	Home Server
	ITALH [198][199]	A	Fall Detection	AMA (#7)	Statistical Functions	Medium	S	Multi	PAN, MD	High	Bluetooth, Zigbee, USB	H. Server, Mob. Device
	COSAR [143]	R	Location-based Recognition	AMA (#10)	MLR and Ontologies	Low	S	Multi	BAN	Low	Bluetooth	Mobile Device
	HS-Care [200]	A	Fall Detection	AMA (#1)	Vision-based Reasoning	High	D	Multi	PAN, MD	Medium	IEEE 802.15.4	H. Server, Mob. Device
	RFID-Track. [36]	R	Location Tracking	AMA (#1)	Genetic Algorithm	Medium	S	Multi	PAN	Medium	RFID	Home Server
	RFID-Behaviour [37]	A	Movement Tracking, Fall Detection	AMA, ADl (#2)	K-means Clustering	Low	S	Single	PAN	Medium	RFID	Home Server
	MHMMR [135]	R	Recognition of Ambulatory Activities	AMA (#12)	HMM	Low	S	Multi	BAN	High	Bluetooth	Home Server
PHM [1]	EMUTEM [201]	A	Remote Health Monitoring	PHA (#1)	Fuzzy Logic	Medium	S	Multi	BAN, PAN	Medium	RF, USB Connection, ZigBee	H. Server, Mob. Device
	ETRI [49][51]	A	Remote Health Monitoring	PHA (#3)	Ontologies	High	S	Multi	BAN, PAN	High	Bluetooth and Zigbee	Mobile Device
	HeartToGo [160]	A	Remote Health Monitoring	PHA (#1)	Artificial Neural Network	Low	S	Single	BAN	Medium	Bluetooth	Mobile Device
	SPA [186]	A	Remote Health Monitoring	PHA (#2)	Data Mining, Time-Series Rules	Medium	S	Multi	BAN, PAN	Medium	Bluetooth, WLAN	Mobile Device
	Dongle [202]	A	Remote Health Monitoring	PHA (#2)	Statistical Methods (QRS)	Medium	S	Single	BAN	Medium	IEEE 802.15.4, Cellular Networks	H. Server, Mob. Device
	AlarmNet [60]	A	Remote Health Monitoring	PHA	Statistical Methods (CAR)	High	D	Multi	BAN, PAN	High	IEEE 802.15.4, X10	Mobile Device
	N/A [203]	A	Remote Health Monitoring	PHA, ADL	Statistical Functions	Medium	S	Multi	PAN,BAN	Medium	Wi-Fi	H. Server, Mob. Device

[1] Ambient Assisted Living, [2] Movement Tracking and Fall Detection, [3] Physiological Health Monitoring

systems which refer to ambient assisted living (AAL). AAL gained a high significance in recent years, it represents pervasive healthcare systems designed within smart environments.

The pervasive and ubiquitous system in AAL may involve standard sensors or specific sensors embedded in the objects of daily usage such as a bed, sofa, or a table. Detecting daily activities and the user's normal and abnormal behavior can be achieved based on the user's interaction with these objects. Several systems and applications were developed to monitor and evaluate the spatiotemporal activities for persons at home and provide appropriate assistive services in a timely manner. These systems address diverse processes which classify activities, recognize particular user habits, detect the behavior patterns, predict the health conditions, evaluate the person's dependency, extract anomalous circumstances and risk situations, and automatically notify caregivers when it is needed. Some other studies focused on the monitoring of specific aspects and assist the elderly and disabled who have some physical disabilities. For instance, to support the visual and hearing impairment [204][205], compensate the movement impairment in smart wheelchairs [206], and develop a customizable speech recognition interface for speech impairment [207].

Basically, AAL systems are designed to monitor and evaluate the user's activity and to maintain the quality of the healthcare service for subjects who need special care for long term periods. AAL timely provides e-health services, keeps subjects (such as patients and elderly) at their own home, improves their quality of life, optimizes their costs and time, and allows them to be as autonomous as possible.

The work in [8] proposed an automatic framework, called Auto-Dep, to evaluate the person's dependency. The proposed service-oriented architecture considers the activities of daily living as defined in the AGGIR geriatric scale [8]. The system provides a context-aware monitoring and evaluation of the person's dependency which allows a caregiver to provide services and monitoring accordingly. In order to monitor the different ADL activities, the work has identified the appropriate sensors for each activity. As a result, a wide set of heterogeneous sensors and equipments was identified including GPS, single inertial sensor, ultrasonic water flow meter, sound detector, flushes switch, light switch, door fridge sensor, hob sensors, dressing door sensor aperture, IP camera and TV. The objective was to cover all the activities considered in the AGGIR model which are classified into internal moving, transfers, elimination, eating, dressing, hygiene, orientation, and coherence. Monitoring raw data of sensors were integrated using a Cilia model, built upon OSGi, where the interactions were ensured using different communication interfaces like Bluetooth, WiFi, Zigbee, and proprietary norms. Context data were represented using the RDF language and then used by an algorithm that performs the person's evaluation. The system automatically fills in the person profile, aggregates the results of any new evaluation of the monitored person and attaches it to the person's profile with a specific date. Dates were used to confront different evaluations and detect possible changes or decline. The proposed system has the ability to notify the changes related to the dependency level of the person and allows him to receive required help and assistance.

Authors in [38] proposed multi-agent service framework called Context-Aware Service Integration System (CASIS). The framework integrates appliances and sensors using Web services for the external support and an OSGi gateway at home. It provides reminder techniques for some health measurements, meals, and medication activities. The work explored how the technology can help to enhance the quality of care by providing context-aware services and healthcare services. The environment is equipped with: (1) *smart floor pressure sensors* where an analog-to-digital converter (ADC) senses pressure changes and translates them into weights. Then, using probabilistic data association and the LeZi-Update [208], the system analyzes translated data to estimate the elderly location ; (2) *a smart table* which contains two layers of a RFID reader/antenna and a weighing sensor. These sensors were used to identify tabletop objects and their locations ; (3) *a smart chair* embedded with bio-sensors to detect some health parameters ; (4) other devices like camera, speaker, telephone and TV. In the CASIS platform, the heterogeneous devices and components packaged Web services to communicate with each other and interact with external services. Each device is connected with a specific agent through device dependent API or network sockets, and then, transforms data into an RDF/XML format. CASIS provides context-dependent services using rule-based reasoning approach addressed by an inference agent. In CASIS, the context event broker implements the publish/subscribe mode, passes the outcome of inference to the device agents then issues these commands to devices. The defined OSGI home gateway is responsible for managing the environment and served as a portal for the outside connection. The proposal of [38] focused on the welfare of elderly lifestyle through modest context-aware information services using an *intelligent telephone* and a reminder. The targeted activities of elder's daily life were limited to location, meal and taking medications.

Another location-aware activity recognition approach, based on ambient-intelligence compliant objects (AICOs), was used in [195]. AICOs used Bayesian-Network-based fusion engine to classify the human activities of daily living and identify how many activities can be detected at the same time. Basically, the system used unobtrusive wireless sensors which were seamlessly integrated into AICOs in order to collect the most informative features. OSGi was used to integrate the variety of wireless sensor networks. Several objects were prototyped to facilitate the interactions with the resident. In order to collect the data naturally, objects were integrated into the home objects which were used by the resident rather than directly on the residents. The project identified an activity map of the human living and included a floor object to identify the resident's location, as well a power object that measures the usage of electronic devices. Although the deployed list of sensors in the living environment, provided services are applicable only to a single resident. The proposition did not consider the most important and dangerous ADL activities that can negatively affect the subject's abilities and dependency.

The system in [152] proposed an estimation of basic activities of daily living using a motion recognition method based on 3D acceleration sensor and ZigBee network. The system is composed of accelerometer sensor tags, access points, a coordinator and a server. The two accelerometer sensor tags are attached to the user's body (hand and waist) and send data to the server via the access point or coordinator. The signal strength indication (RSSI) of the sensor was used to detect the device position according to the distance between the sensor devices and the access point (or coordinator). The server estimated the motion based on the acceleration data. It uses fuzzy inference and area recognition (based on RSSI) and selects the fuzzy membership function and the rules according to the recognized area. Eleven activities and events were selected from ADLs using the estimation based on the sensed data and the recognition of areas. The authors underlined the complexity of estimating the activities; hence they limited the scope to only three activities in the living room.

The Context Aware Real-time Assistant (CARA) framework was proposed in [165]. CARA is a context-aware hybrid reasoning framework that integrates fuzzy rule-based reasoning with case-based reasoning (CBR) for pervasive healthcare in smart home environments. The proposed reasoning framework aims to handle the uncertain knowledge and used the context in order to provide: (1) a continuous contextualization of the person's physical state, (2) a prediction of risky situations, (3) the notifications of emergency situations representing a health risk, and (4) home automation or user prompting within a smart home environment. Particularly, CBR addressed the problems of incomplete data and was used to detect conditional anomalies for home automation. Fuzzy rule-based reasoning handled uncertainty and vagueness of data and achieved query sensitive case retrieval and case adaptation. Wearable and environmental sensors were used to collect raw numeric data. Real-time vital signs of the patient collected by wearable sensors (BioHarness sensors) included several biomedical parameters like heart rate frequency, pulse oxygen level, systolic and diastolic blood pressure, body temperature, and respiration rate. The environmental sensing has been simulated. It involved time, space and duration and was associated with temperature, light, noise, humidity, TV, cooker, phone, status of heater and windows. All measured data were sent to a gateway through a Bluetooth connection. The gateway is connected to the CARA cloud server over the Internet. The reasoning applications run on the home gateway and on a healthcare server belonging to a private cloud environment. In CARA, the data raw are processed by the data fusion services which produce low-level context and build case queries and fuzzy sets. Then, the case-based and fuzzy rule-based reasoning starts running at the same time. The case-based cycle includes the following operations: retrieve, reuse, revise and retain in order to perform the anomaly detection and home automation. The fuzzy rule-based generates a high-level abstraction of the context and identifies the current situation which can be normal, abnormal or emergency. However, in spite of the proposed hybrid context-aware reasoning system, the results have been confined to a limited set of activities for the system's evaluation of effectiveness and efficiency.

A home monitoring system was developed in [196] [104] to monitor and evaluate the well-being of elderly living alone at home. The system consists of two main functions which are activities recognition [196] and forecasts of the behavior [104] in order to determine the wellness of elderly. These two functions rely on a time-series analysis of durations related to the use of household appliances connected through various sensing units. Sensor units were attached to various appliances and connected through the wireless sensor network using a ZigBee module. Six electrical sensors were connected to microwave, toaster, water kettle, room heater, TV and audio devices. Four force-based sensors were connected to bed, couch, dining chair and Toilet. In addition, one contact sensor was used for grooming and one temperature and humidity sensor was used to monitor the ambient environment readings. Along with the hardware level, the software system continuously reads and analyzes the collected data at a home server. Activities like sleeping, meals preparation, eating, toileting, grooming and watching TV were recognized based on the frequency and duration time of appliances usage. As well, the wellness functions were checked based on the active and inactive duration of the appliances. However, in spite of the system was easy to apply, there were no ingredients to provide an adequate and deep knowledge about the elderly and no considerations of the environmental conditions for the purpose of assessing the elderly. Relying only on durations is not enough to efficiently determine the wellness and understand the complex human behavior. Furthermore, the experimentation results in [104] reveal that the forecast process and wellness functions were not accurate during the initial trial period (8 weeks) and the time series modeling is only possible with a minimum of 50 duration observations. Moreover, in spite of the system is easy to apply, but it does not have the ingredients to provide adequate knowledge of the elderly context and unable to note all the environmental conditions for the purpose of assessing the elderly.

The objective of the work presented in [197] is to propose an activity recognition system for ADL detection using small, low-cost, non-intrusive, non-stigmatize wrist-worn sensors. In particular, they used three types of sensors namely accelerometer, temperature and altimeter sensors. These sensors were embedded on a normal sport watch worn on the wrist of the elderly. The watch had an integrated wireless transceiver used to communicate with the computer through a USB RF access point. The system targeted the detection of nine daily activities including the ADL category, such as walking and sleeping, and the IADL category such as washing dishes and watching TV. In order to achieve a high performance of accuracy, different classification models were compared based on MLP, RBF, and SVM. The results indicated that SVM was the most powerful classification algorithm so it was selected for detecting the activities fo the elderly. Moreover, the experimental results revealed that the accelerometer was the most valuable sensor among temperature sensor and altimeter for recognizing the activities. However, it was noticed a system confusion between some activities such as dressing, ironing, brushing teeth and washing dishes. For dressing, there was no clear pattern on how this activity should be performed. This has proved to be challenging especially in finding generalized decision boundaries. For the other three activities (i.e. ironing, brushing teeth and washing dishes), the results assumed that these activities have some common characteristics, which in turn confused the classification process.

A system of self-organizing map for smart home activities recongnition was proposed in [145]. It was based on a self-adaptive neural network algorithm called Growing Self-Organizing Maps (GSOM). The computational approach aimed to analysis the person's ADL and to pattern the activities discovery. GSOM addressed a list of ADL activities such as toileting, meals preparation, grooming, going out, dressing, laundry, cleaning, bathing, washing TV, washing hands, moving, and washing dishes. The learning process starts by generating an initial network, composed of four neurons on a two-dimensional grid, followed by an iteratively presentation of training data samples. Activities recognition and detection carried out in this research were based on the analysis of data collected using a set of small state-change sensors. Sensors were installed on daily objects (like doors, drawers, refrigerators, stoves, sink, light switches, and containers) and electronic appliances (like washing machines, dishwashers, and coffee machines). In sum, 76 sensors were installed on 28 objects of daily usage and were distributed around the apartment during a short period of two weeks. Like other neural network-based techniques, GSOM depends on several predefined parameters such as the initial learning rate and the size of the initial neighborhood.

In AAL and ADL monitoring systems, it is very important to identify the activities required to be monitored. In most studies, the motivation behind the selection of the activities was not provided and present studies mostly address a small number of the ADL activities while others consider some events or subsets of specific activities (e.g. washing dishes or tooth brushing) as the main activities independently to the person's context and need. We also observed modest attempts to consider the IADL (instrumental activities of daily living) category of activities. Part of the explanation lies in the lack of a true understanding about the activities that should be adopted in the health applications and systems monitoring. Furthermore, the adaptability limitations and lack of flexibility in existing approaches lead to a limited and narrow range of selected activities. In our previous investigation [209], we provided a better understanding of the context of monitored persons. We clarified the set of activities of daily living that should be monitored in e-health monitoring systems, and show how they affect the performances of health monitoring systems.

2.8.2 Movement Tracking and Fall Detection

Mobility and accidental falls are common causes of serious damage of which likely leads to the loss of the subject's life. Several projects focused on fall and movement detection besides location tracking in both indoor and outdoor. In HMS, robust and immediate falls detection is important to deliver appropriate services and medical support. The main target of the existing projects and researches is to provide alerts to caregivers when the event of a fall accident occurs, and to enable a remote monitoring to facilitate rapid intervention in emergency situations. Mainly, movement and fall detection systems are targeting ambulatory activities including dynamic (e.g. walking inside-outside and up-down, running, and jogging), stationary (e.g. standing, sitting and lying) and transitional (e.g. sit-to-stand and stand-to-sit, stand-to-walk) activities, as well as location tracking and accidental falls. These systems use PSN and MD sensors and devices for data acquisition (section 2.3.1).

According to [210], based on the selected approach, the used devices in this class of monitoring can be divided into three categories: wearable-based, ambient-based (i.e. sensor-based approach) and camera-based category (i.e. vision-based approach), see section 2.5. Wearable detection approaches use sensors, such as accelerometers and gyroscopes, to detect and measure motion, location, and posture by measuring the acceleration and orientation [161] [211]. Ambient detection approaches use devices such as pressure sensors and PIR for movement detection [212]. They also rely on audio and vibration data analysis [213]. The camera and vision detection approach, implemented in video tracking systems, relies on video data processing such as inactivity, shape and 3D motion for movement and fall detection [200] [58].

The ANGELAH (AssistiNG ELders At Home) framework, proposed in [58], aimed at ensuring elders in-house safety, in terms of monitoring, emergency detection, and networking solutions. Two main design principles were considered in ANGELAH: the context-awareness and the group-based collaboration. The used middleware-level solution aims to integrate sensors and actuators required to monitor and guarantee the elder safety, detect possibly dangerous situations, and compose emergency response groups. Groups are composed of volunteers and caregivers, allocated in the nearby, who are willing to help in case of emergency events. In the ANGELAH architecture, a variety of actuators and sensors are involved: video cameras, RFID readers, sound sensors, and appliances such as a smart door lock, microphones, and speakers. Devices are placed in a way that enables the elder interaction with the system. All the monitoring devices are integrated on top of the Open Service Gateway initiative (OSGi) infrastructure. They gather raw context data and communicate data to the home manager (HM). The context information coming from sensing sources is analyzed by HM using computer vision techniques and Gaussian Mixture models to detect abnormal situations. HM wirelessly broadcasts emergency notifications to the surveillance center (SC) when an emergency situation is being detected. ANGELAH followed the multi-attribute decision-making algorithm (MADM) [214] in order to select adequate volunteers among a group of individuals who want to provide assistance in emergency situations. The ANGELAH framework was designed and implemented for a case study which invloves an elderly affected by severe vision impairments. The system mainly targeted tracking the elderly location and detecting abnormal behaviors such as falls or unusual activity/inactivity patterns along with mobile groupware collaboration supports for assistance. ANGELAH addressed the tracking of a single occupant location. Although it aimed to expand the assistance providers, it did not take into consideration the integration of the available sources and services correlation in the smart home environment.

Information technology for assisted living at home (ITALH) [198] is a wireless home health system designed to remotely monitor patients and to provide caregivers with alerts related to the events of accident fall or acute illness. The project integrated a sensor architecture, called SensorNet, which is a heterogeneous wireless network that connects the home sensor devices and the sensors (worn by the user) to a central home gateway and a mobile gateway. Considered sensors have processing capabilities that allow them to perform analysis, send alerts to the user, and transmit occasional information to the central system when they detect a significant event. SensorNet supports Bluetooth and Zigbee wireless technologies as well as hard-wired connectivity via USB. The project relied on the home wireless (called fixed) sensors and wearable sensors. Fixed wireless sensors are connected to the wearable sensors and to the home and mobile gateway. The mobile gateway is in turn connected to the home gateway. Fixed sensors monitor the subject's environment and measure and analyze the patient's motion. Used fixed sensors were *Telos Rev B Mote* devices [215] that support Zigbee (IEEE 802.15.4) and provide built-in temperature, humidity, and light sensing. For the wearable category, the system used the *Berkeley* fall sensor [216] which is an accelerometer-based fall sensing device. This sensor has a processor capable of analyzing incoming data and classifying motion events such as falls or other normal and abnormal events. Alert notifications related to abnormal situations were sent from the sensors to the home and mobile gateways which fuse the data and determine an appropriate response. The two gateways connect the home network to the outside using the Internet and the telephone service to transmit alerts to caregivers.

Another system, called COSAR (mobile context-aware activity recognition), was proposed in [143] and used statistical and ontological reasoning under the Android platform. The system was developed to recognize ten ambulation activities like brushing teeth, strolling, and writing on a blackboard. Data is acquired by one accelerometer, embedded in the phone, and another one mounted on the individual's wrist. The user's physical location was tracked thanks to a GPS receiver. In their experimentations based on these considered data, the authors selected the MLR (multiclass logistic regression) statistical learning algorithm among other techniques such as bayesian network, C4.5 decision tree, naive bayes, and SVM. MLR provided a recognition rate higher than 80%. However, the *location* dimension was the only context dimension that connects the proposed system to the context-awareness filed.

The smart home care network [200] is a multi-modal sensing application for fall detection and person locations. The proposed system was designed to confirm fall situations and reduce the rate of false alarms. The system includes a user badge node equipped with accelerometers, voice transmission module, cameras, and wireless communication functions such as radio-based triangulation and position estimation using network the nodes. Basically, the system characterized the fall detection using the accelerometer along with the received signal strength (RSSI) between the user's badge and network nodes in order to approximate the position of the elderly. The image sensing and vision-based reasoning have been used to analyze the situation and determine the user's posture when an alert occurs. The badge node broadcasts an alarm message (SMS) to cameras when it detects changes in the accelerometers' data. The image processing algorithms run on the local nodes in order to confirm the fall detection. If a fall is confirmed, the phone dials a stored number to make a call to the care center.

An RFID-Based indoor tracking system for elderly was proposed in [36] to identify the person's location at home. The system comprises a wireless accelerometer to determine if the subject is walking, an active RFID reader with a signal strength function, and RFID reference tags placed in the environment to determine the probable locations of the resident. The system defined two modules: the data manager and positioning manager. The data manager is used to filter out the noise from sensor data, establish the walking paths, and determine the number of walking steps using the three-axis acceleration values. The positioning manager accesses the environment data and uses the RSSI values of reference tags and walking paths to identify approximate regions. Then, based on the RFID values, number of steps and approximate regions, the positioning manager applies a genetic algorithm to compute the probable locations of the inhabitant. Similarly, an indoor U-Healthcare system proposed in [217] used RFID to estimate and track the elderly location. Sensed location data were associated with time slots and the time length of stay in a given place. The system provides new useful information such as movement patterns, ranges, and frequencies.

RFID-based human behavior modeling was introduced in [37] to detect the abnormal behavior of elderly according to their movements. The proposed system deployed several RFID active tags in the living environment and included a notebook PC, a wireless AP and a mobile device (with a built-in RFID reader) carried by the elderly. Thanks to the deployed tags, the RFID reader detects RSSI values which denote the distance between the tags and the reader. These values are recorded following the movement of the person. A clustering technique was used to model the user movements belonging to a normal behavior. The system functionalities were divided into three parts: environment settings and data collection (i.e. transmitted and received RSSI values), data preprocessing (reducing RSSI noise and instability), and behavior modeling by clustering. The latter considered two models for short-term behavior and long-term behavior. The short-term model is used to detect anomalies like falls during seconds while the long-term model is used to detect long abnormalities like those related to toileting and eating. Unfortunately, the system is not accurate to evaluate the subject's overall behavior and performance related to the achievement of addressed activities (e.g. the person's behavior related to toileting and eating). Many devices were used to obtain only one signal which represent only one contextual dimension and can not be used to observe the overall human behavior and judge if the situation is really abnormal.

An unsupervised approach for human activity recognition based on raw acceleration data of inertial wearable sensors was proposed in [135]. The proposition was motivated by the problem of automatic recognition of physical human activities using on-body wearable sensors in a health-monitoring context. Human activities were classified using three accelerometer sensors attached to the chest, right thigh, and left ankle. Twelve ambulatory activities (dynamic, static and transitions) were studied which are stairs down/up, standing, sitting down and related transitions, lying and related transitions, standing up, and walking. The proposed method is based upon joint segmentation of multidimensional time series using a HMM in multiple regression contexts. Mainly, the advantage of this approach comes from the fact that the statistical model takes into account the regime (activity) changes over the time through the hidden Markov chain. Moreover, using this statistical model, the learning is performed in an unsupervised framework using the expectation-maximization algorithm where no activity labels are needed. The proposed algorithm, however, assumed that the number of activities is known. On the other hand, the system attaches several sensors to the body which overburdens the monitored subject, may decrease the subject's mobility, and even obstruct the achievement of daily routines.

2.8.3 Physiological Health Monitoring

Physiological health applications are the most widely studied applications of ubiquitous healthcare systems in smart environments. These e-health applications have first arisen to address hospital related issues. However, with the increasing related needs, the number of elderly people, and the development of information and communications technology, there has been an expansion of new systems into the home environment. Physiological applications emerged for the continuous remote monitoring of human physiological activities. They capture and transmit important vital signal parameters such as heart rate, blood pressure, arterial saturation of oxygen, body temperature, and blood glucose level. These parameters are usually used for further evaluations and interaction in the case where abnormal conditions are detected. Hence, the system allows healthcare providers to monitor the medical status of the subject and immediately provide required services. In this category of applications, most studies and prototypes share the same functionalities and properties like collect, capture, store and send the context in terms of vital signs. Moreover, these applications are facing the same challenges collectively, such as reliability, intrusion, networking infrastructure, and energy consumption. Proposed systems are usually based on body sensor networks (BSN) which connect wearable sensing devices (such as shirts and belts) for data acquisition [50] [49]. In some cases, built-in type of sensors are designed for house objects like the called *u-Devices* used in [218] for different objects (e.g. bed, couch, and toilet). These devices measure the patient's signal and transmit the digitized patient's health information in a ubiquitous way.

An automatic in-home healthcare monitoring system, called EMUTEM, was proposed in [201]. The proposed telemonitoring system is a multimodal platform for the monitoring of elderly and detection of distress situations. The system consists of several sensors such as: microphones placed in all the rooms of the house allowing a remote monitoring of the acoustical environment, a wearable device called RFpat capable of measuring physiological data (ECG), contact and temperature sensors, and a set of infrared sensors that detect the person's presence, posture and movements. The system processing is based on the behavioral and physiological data, the acoustical environment, environmental conditions, and a medical knowledge. Used sensors are connected to a home server. For the audio monitoring, microphones are linked directly to the server through an external sound card. Infrared sensors are fixed on specific places of the house (walls and ceiling) and linked via a radio frequency communication to a receiver connected to the server via a USB port. The wearable device is carried by the elderly and continuously monitors physiological data. It retrieves these data for an indoor reception base station via ZigBee. The novelty of this research lies in the use of multimodal data fusion approach based on fuzzy logic with a set of rules directed by medical recommendations. This multimodal fusion increases the reliability of the system and allows detecting several distress situations.

Authors in [49] and [51] developed a wearable context-aware system and designed a tool for ubiquitous healthcare services in a systematic way. The work proposed an ontology-based context model, using the Web ontology language (OWL), and a reasoning engine to convert the preliminary sensor's context data to high-level contexts. The system consists of a set of wearable sensors, a watch and chest belt system including an electrocardiogram (ECG), a photoplethysmograph (PPG), a skin temperature sensor (SKT), and three axis acceleration sensors. A Zigbee communication module was used for measuring and transmitting pulsation and respiration. Bluetooth communications were integrated in order to link the system to commercial medical devices for measuring blood pressure, blood glucose level, and body mass index. Wearable sensors and devices gather biological signals and were connected to a personal digital assistant. The assistant holds and processes biological signals and communicates with the home server for some additional processing such as database queries. The proposed system is very similar to many modern applications existing in smartphones. Thanks to the various sensors, it allows users to perform self-health check based on the vital signs sent from sensors to the assistant, then the results are sent to the service provider. However, the system is still depending on a strong human interaction for both users and service providers to determine the user's medical health situation.

HeartToGo [160] is another mobile device-based wearable monitoring system. It was designed for continuous monitoring and real-time recording of ECG data. The system detects abnormal patterns related to the cardiovascular conditions and generates individualized health summary report. HeartToGo proposed an artificial neural network-based machine learning technique to identify ECG features and search for cardiovascular potential conditions. The system uses ECG sensors connected to the mobile device using a Bluetooth connection. Unfortunately, the system targeted single vital signs for the individual's physiological conditions independently to the global context of the subject.

A smart phone assisted chronic illness self-management system (SPA) was proposed in [186]. The proposed prototype aimed to provide continuous monitoring for elderly and disabled persons and to reduce, as much as possible, the involvement of healthcare professionals. Basically, the SPA system defined three main functions. First, sensing and monitoring the biomedical and environmental data. Second, data analysis and data mining algorithms were used to identify time-series rules and relationships between collected data. Third, an automatic triggering of on-line surveys and alarm notifications. The SPA architecture uses a smart phone with a GPS sensor to provide context-aware location data, a set of biosensors such as pulse oximeter and blood pressure meter, and a set of environmental sensors such as sound, temperature, humidity, and light. The communication with sensors is achieved using Bluetooth. The smart phone works as a base station for the body area sensor network and communicates with a remote server either using the wireless LAN or the cellular network based on their availability. The remote server stores all the sensed data and deploys data mining algorithms to discover time-series patterns and rules. Algorithms are applied to identify unusual data such as dramatic changes in the sensor readings. For the validity of obtained data, SPA used the technique of the questionnaire-based surveys sent in a textual format using the phone. Determined rules were mined after collecting sufficient data to assess the subjects stress, activity, and environment. However, the proposed system is still in the early stages and needs further proofing results.

A mobile healthcare monitoring system, described in [202], was introduced to monitor physiological signs of patients. For the transmission of data, the network topology is based on a wireless LAN and the code division multiple access (CDMA) cellular network. The system's architecture consists of ECG sensors which gather vital signs and directly transmit them to the server existing in a medical center through a 802.15.4-based access point. When the sensors are outside the LAN coverage and a mobile network coverage is available, the system stores and transmits ECG data to the cell phone using mounted wireless dongles. The cell phone is able to locally perform simple ECG analysis using the QRS detection algorithm

[219]. When abnormal ECG signals are detected, related data are transferred to a server through the CDMA cellular network. However, the limitations of phone resources, processing, and memory prevent the performance of complex operations. In addition, the system considered only simple ECG analysis and provides basic information. A similar work with multi-sensing capabilities was discussed in [220]. It proposed a medical supervision system with two transmission modes: home mode and nomadic mode. The work defined a three layer-based network structure. First, the body bio-sensor layer which collects the bio-data. Second, the transmission layer to guarantee the network connectivity. When the subject is at home, the bio-data are transferred to the nearest wireless local node or to a mobile device for the outside. Finally, the third layer is responsible for the aggregation and analysis of bio-data in a medical center. The results can be then delivered using the mobile phone or Web services.

A user-friendly system was proposed in [203] to provide telemedicine services for elderly and disabled at home. The system was designed to capture vital signs, some human activities and location to allow caregivers to interact with the person and provid possible help. The system focused on the health related data operations like data storage, update, and access. The architecture consists of physiological and ubiquitous sensors. The first category of used sensors consists of medical wearable sensors including pulse oximeter and blood pressure sensors. These sensors were implanted on a wheel chair for capturing the vital signs of the elderly which are sent, upon request, to the caregiver. Sensed data are sent, through WiFi, to a database server. An emergency push button was designed for sending an emergency message through a GSM modem. The second category of used sensors includes weight sensors, motion detectors, and light sensors. They are used to gather context-aware information to track the location and detect some activities. The system provides a Web interface used by the caregiver to monitor the elderly. However, the system is still limited regarding the human interaction for both patients and caregivers. On the one hand, the subjects are obliged to use the wheel chair to enable the vital signs collection. On the other hand, the caregivers still need to access the system, request vital signs data, and analyze medical reports. Concerning the activities of daily living, the project discussed modest context information by only focusing on scenarios where the elderly is going to bathroom and kitchen at night only.

The AlarmNet prototype, presented in [60], is a wireless medical sensor network system designed to monitor the physiological and some environmental conditions. Five main components were used: mobile body networks, emplaced sensors, gateway (*AlarmGate*), back-end, and user interfaces. The mobile body network is composed of sensors used to provide the physiological monitoring. These sensors, like ECG, pulse, blood pressure and oxygen saturation, were developed in the CodeBlue project [118]. Emplaced sensors are used to provide environmental information and resident location tracking: temperature, dust, light, motion and tripwire sensors. The AlarmGate connects different wireless sensors with the IP network. Data are streamed, either directly or in multi-hops, to the AlarmGate gateways for storage, analysis, or distribution to the user interfaces. The major aspects of the AlarmNet system were privacy, energy management, data access, and security. Data are stored in the back-end for long-term in order to analyze and learn the behavior patterns. To do this, the system uses the Circadian activity rhythms (CAR) algorithm [221]. The graphical user interface was used to allow caregivers to query sensor data and display the measurements of the physiological and environmental information.

2.9 Ongoing Challenges and Open Issues

Providing healthcare and monitoring services in smart spaces is a huge domain covering several concepts and raises multiple challenges and issues. The essential goal of the proposed systems is to collect high relevant data, that are tied to the person's context, in order to provide evaluations, diagnosis, treatments, quick decisions, and relevant services. A lot of issues and challenges still need to be addressed and require further improvement including software applications, hardware, and network communication. Based on the previous survey, we discuss in this section the most important issues and challenges facing the health monitoring systems in several aspects.

2.9.1 The Accuracy and Authenticity

Monitoring and evaluating human subjects, in particular elderly, is a complex task due to the complexity of the behavior in performing different daily activities. A behavior is different from one individual to another and can be changing with the same person according to mood swings and health conditions. Most of the current studies related to the monitoring of activities focus on relatively simple activities that are performed in short periods within a laboratory environment. In the real world, however, complex activities and those executed over a long-term period are clearly more difficult to manage in terms of collection and analysis of relevant data. Moreover, activities which have several sub-actions can be performed in different ways and several orders. Long-term monitoring is useful for detecting the real behavioral patterns of a person in a smart space. In the existing research experiments, data is collected and analysed for the activities of a single user in the smart environment. However, in reality, the daily activities can be concurrently performed by multiple users who share the same space.

Existing interactions between users can hide the real ability of the person to perform ADL and increase the complexity of monitoring. Therefore, considering the monitoring of multiple users is more challenging and difficult task. In addition, the most research in this realm is focused on recognizing activities rather than evaluating whether the person performs these activities correctly or not. According to these challenges, the accuracy and robustness of the results are still relatively far from the real world properties in which the human behavior is mysterious and variable. We believe that there is a need for more efforts to improve the design and development of monitoring systems for elderly in smart environments. In such desired systems and solutions, appropriate sensors should be carefully selected to capture rich and relevant data for single or multiple users. The system should identify suitable methods and techniques that can effectively be able to understand the complex and changes of the human behavior. Such system must be tested for long-term periods and ensures its effectiveness in terms of analysis, accuracy, and adaptability of the proposed monitoring. Hence, the system can provide relevant services based on the person's context.

2.9.2 Context-Awareness

A healthcare context-awareness system provides users relevant, suitable, and personalized applications, interfaces and services matching their context and evolution. The full visibility of the person context permits to dynamically determine the person's real needs in terms of assistance and help. In HMS, it is important to correctly interpret collected data and events in order to extract a coherent high-level abstraction of contextual data. In addition to the classic monitoring, emergency situations and the deterioration in the health status should be reliably detected earlier. Mainly, the design of context-aware healthcare applications faces two major challenges which are data acquisition (which information is worth capturing) and data analysis techniques including the presentation of contextual information and services [222]. The representation and context-aware interpretation of data are the key aspects influencing the success of a health monitoring system. An accurate detection of emergency situations allows rapid interventions and, therefore, improves the healthcare quality for persons. For instance, according to the person's context and conditions, not all the person's detected falls represent critical cases, need a system reaction, or caregiver intervention. In existing systems, despite there are many attempts to reach a high degree of context-awareness, full and complete contextual information still a critical open issue which need further attention.

Earlier design of context-aware monitoring systems should consider the functionalities of observation, interpretation, and reasonning about the patient's conditions in different aspects: behavioral, physiological, and environmental. The system must consider all the relevant contextual dimensions which consist mainly of location, time, objects, posture, frequency and the human activities being performed. Historical data including health records (like diagnoses, diseases, and treatments), current daily behavior and previous changes, and the environment conditions (like temperature and humidity) also influence the system's intelligence. Healthcare systems must be able to determine what, when and how to monitor, gather and analyze data related to the person's context [223]. On another front, the same context data should be available on several distribution components using different network technologies. This enables different caregivers to obtain required context information from the infrastructure using the available network that can vary in a pervasive environment [58]. A context-aware handover mechanism was proposed in [87] in order to provide the capability of selecting the suitable network interface for the data transfer.

Although a variety of sensor technologies are widely available today, context-aware systems for health services do not fulfil the desired requirements and there are many aspects which need further improvement. In spite of the several studies and healthcare applications which have been proposed on context-aware computing, there are still other open issues and challenges such as the lack of recommendations for functional needs of the context, gap between fundamental context representation and actual context awareness prototypes and the difficulties in building efficient system to simulate the human perspective [30].

2.9.3 Human Factors

One issue of great importance is the consideration of human factors such as the human acceptability of a given system and the degree of supported human interactions with the proposed system. The consideration of human factors and human-computer interaction (HCI) contributes in optimizing the human well-being and overall system performances [224]. At the design level, these factors focused on the understanding of interactions between the user and the developed system components. In the healthcare realm, the need to characterize these interactions have been addressed by some studies, such as [225] and [226], in order to fulfill the needs of elderly.

The human factors should be considered to design systems that improve the quality of healthcare, consider the minimization of errors and increase the system's adoption by the user. Specifically, factors aim for effectiveness, efficiency, and patient satisfaction in the design of a health monitoring system [227]. This consideration is of paramount importance especially for aging populations who do not necessarily have the desire to use modern and complex technologies [228]. Moreover, elderly suffer from age-related health issues (e.g. declines of cognitive abilities), which prevent them from learning and adopting new technological solutions [229]. This kind of factors has been considered in the context of designing elderly monitoring solutions in some studies such as in [31], [227], and [230]. We believe that the *usability* and *acceptability* are the most important factors to be considered for both monitored persons and the caregivers in HMS [31] [231–233]. Unfortunately, these factors were ignored in the majority of studied works and are worthy of particular attention.

2.9.4 Heterogeneity

Health applications need a variety of contextual data which are gathered using different and heterogeneous sources. In HMS, the heterogeneity is mainly observed in two forms: heterogeneity of data and heterogeneity of sensors. Data are collected from multimodal sensors are heterogeneous in formats, structures and semantics. Thus, datasets are difficult to share and reuse due to the lack of a formal description. Although the efforts made to develop sensor data models, used to describe the semantic, there is a need to normalize the sensor data modeling to represent heterogeneous data sources.

The integration of several heterogeneous sensors that operate at different frequencies and use different network protocols raises the problem of interoperability. There are numerous studies which explored related heterogeneity issues over HMS [234][235]. In [235], the main identified issues were the integration of heterogeneous devices in a single network, the lack of a common architecture supporting different devices and the difficulty of integrating HMS with other systems. Prior attempts to solve the heterogeneity problem have been made and various solutions were explored. One of the proposed solutions at the application level is the middleware design (discussed previously in this Chapter). As explained, middleware help to manage heterogeneity and provide abstraction between applications and sensors to simplify the application development. For instance, the MPIGate gateway [234] integrates multi-platform systems in a unified framework and offers a modular and transparent data access. The unified framework allows the interconnection of heterogeneous networks and existing middleware solutions. Another middleware, proposed for wireless medical body area networks [236], was able to support multiple sensors and applications with the plug and play feature and resource management.

The combination of sensors and devices in HMS can generate a high level of interference among them. The interferences and overlap of ranges caused by the coexistence of several wireless networks can significantly affect the reliability of the healthcare network system and hence the availability of critical data [237] [238]. Existing experimentations show the impact of interference on received data rate [239] [240] and the increased delays and power consumption [241]. Some existing strategies were proposed to address these related issues, such as the coexistence of ZigBee and WiFi for HMS [242][243][244], the coexistence between Bluetooth LE and technologies using the same spectrum [245], the overlapping of wireless channels using allocation schemes and algorithms [246–250]. The schemes proposed in [251][252][237] aim to provide a reliability in the transmission of critical health monitoring data.

Nevertheless, the experimentations of previous studies and solutions have demonstrated other problems such as those related the additional delays and consumption of resources. There is still a need to find new schemes and strategies that mainly guarantee the support of heterogeneity with good performances, the simplification of architectures, protocols and normalization of used data formats and presentations.

2.9.5 Availability and Reliability

The accessibility of correct health data in a timely manner is a further critical issue in HMS. The degree of availability of health information could negatively impact critical situations of the person which in turn is influenced by the reliability of data delivery. Data reliability in health infrastructures relying on wireless networks is subject to a number of factors. The main factors are the network coverage, device range, available power, routing protocol, and failures of the network or devices. Reliability issues have been already classified into three main categories: data measurement, data communication, and data analysis [69]. Numbers of studies addresses the issues in health monitoring over wireless transmissions, for instance, using redundancy elimination [253] and data cleaning [69].

A data coding and transmission method was proposed in [253]. It includes two coding stages: compression and inflate. The first stage is used to compress the natural redundant information and the second one is used to inject artificial redundancy into the wireless transmission to enhance the transmission reliability. Hence, after data sensing and coding, the wireless sensor nodes transmit the coded data instead of the sensed raw data. Authors in [69] described the healthcare monitoring issues with a focus on software problems including data collection, data fusion, and data analysis. Thus, they proposed an architecture for handling data cleaning, data fusion, and context and knowledge generation for more reliable data analysis.

It was observed that in HMS, the number and complexity of sensors and used methods is significant if compared to traditional infrastructures. In addition, the heterogeneity of data sources (discussed previously) adds a greater level of complexity that must be taken into account to have reliable data from any source. Existing sensors still limited in terms of hardware and software capabilities, hence they can be subject to failure at any time. Consequently, considering robust fault-tolerant strategies is very much needed in HMS.

2.9.6 Data Transmissions

A common challenge in the development of monitoring systems, especially in WBAN applications, is to select the way in which sensed data should be transferred to back-end servers responsible for the analysis and processing. In networking, data transmissions are categorized into four schemes: multicast, broadcast, unicast, and anycast. Existing HMSs often use the multicast or broadcast scheme to increase the reliability and optimize the data transmission. Both schemes deliver, at one time, packets to multiple receivers. Hence, frequent transmissions lead to a high network traffic and transmission delay. The unicast scheme, where packets are delivered to a single receiver, has the least traffic overhead but requires additional procedures to find out another receiver in case of transmitter failure. The anycast communication mode is a new routing approach where data packets are routed to the nearest receiver. This scheme has a lower traffic overhead compared to broadcast and multicast and it is more reliable than the unicast in finding new receivers. However, the anycast increases the complexity of the network routing and used devices.

Improving the message delivery in HMS over wireless ad hoc networks was discussed in [254] by using several routing schemes. In [255], a reliable transmission protocol, based on the anycast routing scheme, was proposed for the wireless monitoring. The sensor nodes select the nearest data sink to transmit messages with vital signs in a ZigBee network. The proposed protocol uses a ZigBee device (accelerometer) for fall monitoring, indoor positioning, and ECG monitoring. When the accelerometer detects a fall, the current patient's position and ECG signals are transmitted to a data sink. In the case of a network path failure, the transmission path is rebuilt from the last node before the failure link. Hence, it provides a reliable communication and reduces the transmission latency as well as reducing the traffic overhead. The framework of the wireless patient monitoring system, discussed in [256], involves the processing of vital signs, routing schemes, and protocols for messages delivery. The performance results show that reliable messages delivery and low monitoring delays can be achieved by using the multicast or broadcast routing schemes.

There are broader considerations arising from this challenge including transmission technologies, the determination of transmitted data amount, regular packets size, transmission frequencies, and power. All of these considerations have a major impact on the system's effectiveness, availability, reliability, network traffic and energy consumption. In HMS, the reliability of data transmissions depends on the range of devices used by the subject itself, cooperating devices integrated into the

HMS architecture, used routers, and target receivers.

2.9.7 Security and Privacy

In HMS, security requirements are the same as those of traditional networks, such as availability, confidentiality, integrity, access control, and authentication [72] [257]. Healthcare monitoring systems heavily relied on several technologies that can pose security threats and attacks such as eavesdropping and modification of medical data, location and activity tracking, forging of alarms on medical data, denial of service, physical tampering with devices, and jamming attacks [70]. Moreover, deploying wireless technologies in healthcare system without considering security requirements often makes patient privacy issue vulnerable [258] [259] [71]. Privacy should also be among the major concerns in e-healthcare applications. The transmission of personal data over the Internet and wireless media could pose serious threats to the privacy of individuals.

The security in health monitoring systems is a critical issue which involves many components and processes: sensors and devices, data collection, and the communication. In HMS, applying security strategies should take into consideration the constraints of the HMS environment such as battery lifetime of sensors, storage of sensed data and historic records, and used network technologies. Since HMS deal with sensitive and critical patient data, existing cryptographic methods (like encryption and authentication) can be used to provide patient privacy and security against attacks. Robust cryptography techniques need, however, wide computation and resources. Therefore, defining or identifying appropriate encryption strategies remains challenging. HMS usually involve huge data collection and processing for continuous monitoring and sensors control. Therefore, there is a need to define optimal methods that can provide maximum security and privacy with a minimum of resources usage. In [260], the authors have raised several interesting questions regarding privacy and security concerns. For instance, where should the health data be stored, who can view a patient's medical record, to whom should this information be disclosed to without the patient's consent, and who will be responsible for maintaining these data.

2.9.8 Intrusiveness

Improving the quality of life (QoL) and making it easier and comfortable is one of the HMS challenges. Wearing and carrying sensors all the time in some proposed applications, like in BSN, is a very cumbersome task and need more efforts to curb violations on the human lives of residents. Some studies addressed part of this problem with the mobility and portability solutions. For instance, TV sets were used to provide healthcare services in [53], a smart shirt which continuously measures ECG and acceleration signals was introduced in [50], and a watch device for motion capture in body area sensor networks was introduced in [48]. Unfortunately, the scope of the provided health services in such attempts and existing propositions is still limited and further efforts must be exerted.

2.9.9 Power Consumption

Energy consumption is another important issue of sensor network applications especially in BSN. The life cycle of HMS can be negatively affected due to the limited battery life of used sensors. Replacement and charging of batteries in most existing BAN systems is an inefficient task and is cumbersome for monitored persons especially in the architectures which include several sensors. Normally, the battery life of any communication mean depends on its duty cycle, transmission range, and the way in which the communication channels are used. In order to save the energy with the widely used MAC protocol, sensor nodes can periodically turn On/Off their radio interface with a centrally assigned time slot [261]. However, the traditional use of MAC protocols has shown inadequate network throughput and delay performance at varying the traffic [52]. Recently, in medical sensor networking, there is a tendency to use the new low-power standard Bluetooth low energy (BLE). BLE allows sensors and devices to operate more than a year without recharging or change batteries [67] [65]. Despite the fact that the low-power issue has been addressed in many previous studies, it is still a significant issue that needs further progress and needs to be solved in HMS.

2.10 Conclusion

Although recent years have seen a plethora of impressive works on health monitoring, we identified the weaknesses of existing systems, main challenges and a number of still open issues. Mainly, most of existing researches in context-aware e-health systems operate in isolation from the requirements of the real world and healthcare institutions. This fact contributes to a high incidence of projects that are either unsuccessful or not adopted [262][263]. Unfortunately, the absence of such link leads to high uncertainty in the adoption of such projects. Moreover, the existing e-health monitoring approaches lack a true understanding of the person's context regarding to the achievement of basic activities of daily living and health status. Therefore, it is important to improve context-aware e-health systems, link them to the real world, and ensure an easy integration of the new proposed e-health systems into health institutions. The work in this thesis aim to improve the effectiveness of e-health monitoring systems and keep a strong link with existing medical methods such as the models used in the geriatric domain (discussed in Chapter 3).

Context-aware assisted living systems must have a global and full visibility of the person's context. This visibility includes the ADL performances and anomalies detection [209]. The important challenge in such intelligent environments is to determine: what, when and how to monitor, gather and analyze data related to the person's context [223]. Most of the health monitoring approaches and context-aware assisted living systems tend to apply unconditional processing on all the collected data. This continuous monitoring approach is resource intensive whatever the person's context. The adoption of such an approach causes several issues such as the collapse of network, data transmission failure, energy consumption, important computational cost, and loss of priorities in processing and making decisions that should be relevant and quick. The same situation occurs with the physical monitoring applications which assume a uniform time interval data sensing and analysis.

The acquired raw data are worthless unless it is interpreted, analysed and understood. Moreover, in reality, the human's behavior is highly dependent on perception, context, environment and prior knowledge [16]. Other important factors that can affect the behavior are the physical and mental states and changes in states such as the perceptual abilities, physical skill, memory, etc. Therefore, a key challenge in a smart system is to find the appropriate methods or algorithms that can effectively interpret the obtained data (low-level) and extract a new context view (high-level) in order to understand the complex and variable human behavior. As presented previously, there are several methods applied for detecting the human behavior and extract the context in health smart environments. The adoption of these processing methods have a decisive impact on the accuracy of the final results, thus it is the foundation stone for the success of the whole system. The accuracy of the system's performance and results represents a relative matter and is influenced by several factors such as type and amount of data used along with type of sensors, number of sensors, placement of sensors and type/number of target activities. All of these factors are still challenging and need more investigation. For instance, in most studied works, the motivation behind the selection of the activities was not provided [9], and there is no standard definition of the targeted activities that should correctly reflect the real health status and behavioral context of persons.

It becomes clear that each used method in HMS has its strengths and suffer from weaknesses. Comparing the performance of these techniques in research experiments within a limited problem domain could not truly reflect the effectiveness of the overall health monitoring system. No single technique can be used to meet and gain perfect results. Given the various facets of health monitoring systems, it appears that the best approach is to combine different methods which complement each other and provide a comprehensive picture of the person's context in a smart space. This combination can vary depending on the nature of targeted activities.

Studied approaches typically require substantial amounts of training data to learn and detect the human behavior and context. Proposed methods can, sometimes, provide a good performance but with high computational cost. There is still a need to improve the smart processing in health monitoring systems in order to balance the optimal monitoring cost and an accurate detection/prediction of the person's behavior [187].

CHAPTER 3

Health Measurements for the Elderly

Contents

3.1 Introduction

The field of health monitoring and human behavior detection is extremely active and a very wide range of approaches to monitor and evaluate the person's behavior regarding the achievement of daily activities is currently being investigated. The evaluation of persons helps to reveal the person's real needs and allows the systems providing timely assistance and services which is the essence and basis of automatic monitoring. Nevertheless, to our knowledge, none of the current approaches systematically consider the person's context (health and behavior) as it is defined in the geriatric domain.

Generally, researches in sensing systems and health monitoring community take whatever is measurable and consider that as the *user's behavior*. Modeling techniques are then used to detect anomalies. When an abnormal behavior is detected, the user is deemed to have been changed regarding its health status. In other words, health and behavioral systems for persons, in particular for elderly, were designed based on the availability of activities sensing without a link to a medical knowledge and a good understanding of the elderly context as defined in the geriatric domain. Hence, most of existing researches in context-aware e-health systems operate in isolation from the real requirements of the healthcare institutions. As mentioned in the conclusion of the last Chapter, this fact contributes to a high incidence of projects that are either unsuccessful or not adopted [262][263]. Indeed, the absence of such link leads to high uncertainty in the adoption of proposed projects. Existing e-health monitoring approaches lack a true understanding of the person's context regarding the achievement of basic activities of daily living (ADL) and health status. Without such a knowledge and understanding, any efforts in improving the quality of healthcare and lifestyle for elderly using smart home technologies would be ad-hoc and can not be expected to provide the desired results.

Therefore, for the human activities, a medical knowledge should be considered in order to validate if the behavior pattern change correlates with the health status change of the person. It is desirable to provide a better understanding of the context of persons in order to provide them with e-health services that meet their context and real needs. Using this knowledge improves the context-awareness and make easier the integration of new proposed e-health systems into the real world and health institutions.

In this Chapter, we describe the person context regarding the achievement of the activities of daily living as defined in the geriatric domain and dependency evaluation models. We provide a better knowledge about the human activities and their characteristics for elderly in a smart space with the aim of a proper sensing and design of efficient monitoring frameworks.

The rest of the Chapter is structured as follows: in Section 3.2, we present an overview of assessment scales used in the geriatric domain for elderly. Section 3.3 describes a list of dependency evaluation models. In Section 3.4, a general taxonomy of activities, in a manner that is meaningful for monitoring systems, and a characterization of activities are presented. Finally, some conclusions are drawn in Section 3.5.

3.2 Geriatric Domain and Assessment Scales

Understanding the elderly health conditions and corresponding measurement scales is crucial and indispensable for developing an e-health monitoring system that detects the behavior patterns and provides a health assessment of the elderly. Assessment models and instruments, used in healthcare of the elderly and patients, cover a wide range of areas relevant to the health and wellness of persons. Generally, in the geriatric domain, there are four main areas used to evaluate the health of an elderly: physical health, functional health, mental health, and social health [264], [265].

- Physical health: the assessment typically includes taking a medicine history (disease-specific) and physical examination such as gait, fall, and mobility.

- Functional health: this aspect is an essential part of the clinical practice. The functional health involves the patient's ability to perform the activities of daily living (ADL) and instrumental activities of daily living (IADL). The ADL refers to the routines and basic tasks performed by persons every day, such as eating and washing. The IADL refers to the tasks required to live in a community such as medication use and budgeting. Basically, ADL are disability-oriented while IADL assess handicap rather than disability. The IADL activities are usually lost before the ADL.

- Mental health: the assessment of the mental health includes a cognitive assessment to determine the mental disorder (e.g. dementia or delirium). The corresponding scales are used to assess the cognitive ability of older people as well as their behavioral competence.

- Social health: these assessment scales examine the person's social health such as economic conditions and the availability of healthcare resources (e.g. caregivers, family, and volunteers).

3.3 Dependency Evaluation Models

The decline in functional abilities with aging leads to a loss of independence. Impairment of functional status could be the first sign of a disease process. Therefore, understanding the functional status is an important component of geriatric assessments [266]. In the geriatric domain, the health status and wellness of persons are measured by the so-called *dependency evaluation* methods. The person's dependency can be defined as the *ability of a person to achieve elementary tasks of daily living without the help or stimulation of a third party* [8]. To assess this ability, different tools and methods have been developed to study results of treatment and prognosis in the elderly and chronically ill [267]. These methods include the determination of what is a *basic* activity of daily living and the methodology of assessment to evaluate each activity. Broadly, most of the existing models are based on the definition of the ADL as introduced by Katz [267], and the instrumental activities of daily living (IADL) of Lawton [268]. Famous models that are widely adopted such as SMAF [269], used in Canada, and AGGIR [270], used in France, define different methodologies of assessment to evaluate each activity. The concepts of the *person's profile* and *group* are usually used in the evaluation methods for the classification of persons based on: needs, assistance, costs, diagnosis, etc. This classification tries to aggregate people having the same characteristics and who need approximately the same level of services and resources. For instance, existing classifiers use the called *iso-resources* group [270], *iso-profile* SMAF [271], FIM-FRG [272], and *diagnosis related groups* [273].

In health institutions, these evaluation models are used to guide the professionals to make the right decisions while providing healthcare with or without monitoring. Most of these models are performed manually. This makes them exposed to human errors and lack immediate alerts in case of any dependency change or decline of the health status of the person. In the context of e-health services and smart home environments, the monitoring, evaluation of the person's lifestyle in performing the daily activities, and detecting the human behavior are of high concern. The geriatric evaluations are very useful in health monitoring systems for supporting the elderly population who suffer from age-related disease such as cognitive decline and chronic diseases including diabetes, cardiovascular disease, Alzheimer's disease, etc. The activities of these persons are influenced by their diseases. For instance, patients with diabetes may have different behavior in performing some activities such as frequent drinking, toileting, and sleeping. Therefore, being able to detect the changes of the human behavior patterns helps to identify the elderly context, diagnosing illnesses, and provide appropriate services.

Existing approaches in e-health monitoring systems lack a true understanding of the person's activities that should be considered in the monitoring. Their lack of adaptability leads to a limited and narrow range of activity selection [209]. Therefore, we believe that in order to provide health professionals with flexible, reliable and smart monitoring systems, a strong link should be kept between the existing medical tools on the one hand and the new monitoring systems on the other hand. This link will help to (a) put the light on the drawbacks of existing medical methods, (b) propose required improvements, and (c) facilitate the integration of new e-health systems into the health institutions (e.g. using existing patient's record, historic, etc).

In this Chapter, we review the most commonly used measurement models in the domain of health and dependency evaluations. We describe the most important concepts in each existing model such as items and evaluation methods. Table 3.1 shows an overview of the measurement models used today in the evaluation of elderly including the main functional abilities, subscales, and items.

Table 3.2 compares the main differences between these models in many aspects. Items are related to the activities used in the models while the classification function returns the whole evaluation of the person based on the individual qualification and scores. Profiles denote the losses of autonomy and give a detailed classification while groups and categories reduce this classification into common sets. A more detailed description will be provided for the most famous models AGGIR and SMAF which have been used in part in the contribution of this thesis.

3.3.1 Katz Index of Independence

Among the instruments used to evaluate basic ADLs, Katz index of ADL is the most known scale in clinical practices. The Katz index was developed by Katz et al. [267, 274], to assess the functional status as a measurement of the elderly's ability to perform activities of daily living independently. The Katz idex includes six items describing the activities of daily living such as eating, bathing, toileting, etc. The considered activities are ordered by difficulty. Elders are scored yes/no in order to evaluate the independence of each item among the six defined items using a 1 point scale of independence and 0 point for dependence. A total score value of 6 indicates full function, 4 indicates moderate impairment, and 2 or less implies severe functional impairment (see Appendix A).

Table 3.1 – Dependency evaluation models used in healthcare

	Models	Main functional abilities	Item within subscales
1	Katz	ADL	bathing, dressing, toileting, transferring, continence, feeding
2	Lawton	IADL	ability to use telephone, shopping, food preparation, housekeeping, laundry, mode of transportation, responsibility for own medications, ability to handle finances
3	Barthel	ADL and Mobility	feeding, bathing, grooming, dressing, bowel control, bladder control, toileting, chair transfer, ambulation, and stair climbing
4	FIM	ADL, Mobility, and Cognitive	I. Motor domain (related to self-care, sphincter control, transfers, locomotion - 13 items): eating, grooming, bathing, dressing (upper body), dressing (lower body), toileting, bladder and bowel managements, transfer to bed, chair (or wheelchair), transfer to toilet, transfer to tub or shower, walking/wheelchair, and moving up/downstairs. II. Cognitive domain (related to communications, social cognition - 5 items): comprehension, expression, social interaction, problem solving, and memory
5	NPDS	ADL, Mobility, and Cognitive	I. BCN (16 items), the 16 items are: ADL (related to Continence, Washing, and Feeding - 10 items): toileting-bladder, urinary incontinence, toileting-bowels, faecal incontinence, washing and grooming, bathing/showering, dressing, eating, drinking, enteral feeding; Mobility (2 items): mobility, bed transfers; Cognitive (4 items): skin pressure relief, safety awareness, communication, behaviour. II. SNN (7 items): including nursing care items
6	AGGIR	ADL and Mobility	coherence, eating, orientation, elimination, hygiene, transfers, dressing, and internal moving
7	SMAF	ADL, Mobility, Communication, and Mental functions, IADL	ADL (7 items): eating, dressing, washing, grooming, urinary function, bowel function, and toileting ; Mobility (6 items): transfers, walking inside, walking outside, donning prosthesis or orthosis, propelling a wheelchair, and negotiating stairs ; Communication (3 items): vision, hearing, and speaking ; Mental functions (5 items): memory, orientation, comprehension, judgement, and behavior; IADL (8 items): housekeeping, meal preparation, shopping, laundry, telephone, transportation, medication use, and budgeting

Table 3.2 – Comparison between dependency models

Models	Katz	Lawton	Barthel	FIM	NPDS	AGGIR	SMAF
Items	6	8	10	18	23	17	29
Functional abilities (subscales)	1	1	1	6	5	1	5
Qualification item	1 or 0	1 or 0	0, 5, 10, and 15	1 to 7	0-3, 0-4, or 0-5	4 (S, T, U, and C)	4 or 5 (0, -0.5, -1, -2, and -3)
Scoring criteria	1 or 0	1 or 0	0, 5, 10, and 15	1 to 7	0-3, 0-4, or 0-5	3 (A, B, and C)	4 or 5 (0, -0.5, -1, -2, and -3)
Minimum level of dependency	<= 2	0	0	126	0	< 2000	-9.33
Maximum level dependency	6	5 (for men) and 8 (for women)	100	18	100	<= 4380	-87
Number of profiles	/	/	/	/	/	13	14
Classification group or categories	3	/	4	3	3	6	4
Achieve manually	Yes	Yes	Yes	Yes	Yes	Yes	Yes

3.3.2 The Lawton Instrumental Scale

This IADL scale was designed by Lawton and Brody [268](Appendix B 7.2). It represents an instrument to assess the independent living skills such as meal preparation, taking medication, and the ability to handle finances. These skills are considered more complex than the basic ADL measured by the Katz index.

Eight items are measured with the Lawton scale scored by 0 for dependency and 1 for independency. Women are scored on all the eight defined areas of functions, while for men, the areas of food preparation, housekeeping, and laundering are excluded. Elderly are scored according to their highest level of functioning. For women, a summary score ranges from 0 (low function or dependent) to 8 (high function or independent). For men, the score ranges from 0 through 5 [275][268].

3.3.3 Barthel Index of Activities of Daily Living

The Barthel index (BI) of ADLs, was first developed by Barthel in [276] and modified later by Colin in [277]. The BI is now widely used in rehabilitation. It measures the functional disability by quantifying the patient performance related to 10 activities of daily life. The BI can be used to determine a baseline level of functioning and can be used to monitor the noticed improvements in activities over the time. In the original version of BI (see Appendix C), the 10 activities are scored using the values 0, 5, 10, or 15 depending on the item. Scores are defined as follows: 0 for *unable*, 5 for *needs help*, 10 or 15 for *independent*. The values are added to give a total score varying from 0, representing a totally dependent person, to the maximum score of 100 indicating that a patient is fully independent. These scores are categorized into four groups [278], < 20: denotes a total dependence ; [20-40]: denotes a severe dependence ; [40-60]: denotes moderate dependence and > 60 which denotes a mild dependence. The Barthel index is suitable to be used as a record of what a person *does* and not of what a patient *can do*.

3.3.4 Functional Independence Measure

The functional independence measure (FIM) scoring system was developed to suit rehabilitative aspects of patients with disabilities. It is based on the conceptual framework of pathology, impairment, disability, handicap, and burden of care [279][280]. The FIM consists of 18 items that assess the patient's abilities across six subscales: self-care, sphincter control, transfers, mobility, communication, and social cognition. The items are classified into two main domains: motor (13 items) and cognitive (5 items). Each item is given a score from 1 to 7 as follows: 1 for total assistance, 2 for maximal assistance, 3 for moderate assistance, 4 for minimal contact assistance, 5 for supervision, 6 for modified independence, and 7 for complete independence. The scores are tallied up for a maximum total score of 126 (completely independent) and a minimum score of 18 (totally dependent). These scores can be categorized into three groups: (1) requiring help or assistance with the scores from 1 to 4 ; (2) requiring supervision (score 5) ; and (3) requiring no help with the scores of 6 and 7 (Appendix D) [281].

3.3.5 Northwick Park Dependency Score

Northwick Park Dependency Score (NPDS) [282], presented in Appendix E, is developed for the assessments of the requirement of nursing time in a rehabilitation setting in order to evaluate the full range of dependency. The NPDS is now widely used in the UK and has also been trialed in other countries [283]. NPDS is divided into two main parts: basic care needs (BCN) and special nursing needs (SNN).

The BCN section (with a score range of [0-65]) includes 16 items within 5 subscales covering the daily activities needed for everyday functioning. These items comprise the capacity for both physical performance of ADL (e.g. dressing, toileting, eating, etc.) and cognitive behavior (e.g. communication and safety). Each item is rated on a scale of 0 to 3, 0 to 4, or 0 to 5. The SNN section (with a score range of [0–35]) comprises 7 care items indicating the need for nursing care such as a wound requiring dressings. These items are scored on a scale of 0 or 5 to reflect the intensity of nursing input that they represent. Overall, the total scores from each section summate to give the total composite NPDS score, ranging between 0 and 100 (65 for BCH and 35 for SNN). Lower scores indicate that the person is more independent. The dependency level of NPDS has been categorized into three groups: Low, Medium and High [284]. In low dependency (< 10), patients are largely self-caring and require only incidental help with ADL. In the medium dependence category ([10–25]), patients generally require help from one person for most of the ADL tasks. In the high dependence category (> 25), patients require help from two or more people for most of the ADL tasks and often have special nursing needs.

3.3.6 Description of the AGGIR Model

The Autonomy Gerontology Iso-Resources Group (AGGIR) is an evaluation dependency model used in France to determine the degree of dependence of an elderly person. AGGIR uses a complex algorithm to calculate the person's dependency. This model considers 17 items describing the activities of daily living. There are 10 discriminated items which have been identified. Eight of them are used in practice during the classification of dependent persons. This creates 13 profile ranks and 6 groups. Like other dependency evaluation models, the AGGIR evaluation is achieved manually by the medical staff. Each item is qualified by the medical reviewer using the four possible adverbs: *Spontaneously* (or S), *Completely/Totally* (or T), *Usually* (or U), and *Correctly* (or C). The S means that activity can be achieved without any stimulation. The T means that all of the actions involved in the activity can be done by the person himself. The U means that the activity is done regularly, the frequency of the execution depends on to the nature of the evaluated activity. The C involves the quality of the person's realization, the safety and the conformance with the recommended usage or achievement of the activity. According to defined logical conditions involving these adverbs, an activity is evaluated with the following modalities: A, B, or C. For instance, a given activity is evaluated with the modality A, if the person can achieve the activity with the following condition: $S \Lambda T \Lambda C \Lambda U$. The A evaluation means that the person is completely autonomous in achieving a given activity, B means that the person is partially dependent, and C means that the person is dependent and cannot achieve the activity alone [8].

The 13 profile ranks of AGGIR refer to a decline in the autonomy of persons. The defined 6 groups, called iso-resource groups (called GIR), reduce the number of profiles and address the needs of assistance. The GIR algorithm computes the GIR number (1 to 6) based on a predefined association between the profile ranks and groups. For instance, the rank 1 is associated to the GIR 1, ranks from 2 to 7 are associated to the GIR 2, etc. (Table 3.3). The first group (GIR 1) represents

Table 3.3 – Association between Profile Ranks, Classification Scores GIR

Profile Ranks	Score Condition	GIR	Description
1	$S_1 \geq 4380$	1	Bedridden or confined to an armchair and mental faculties severely impaired.
2 3 4 5 6 7	$4140 \leq S_1 < 4380$ $3390 \leq S_1 < 4140$ $S_2 \geq 2016$ $S_3 \geq 1700$ $1432 \leq S_3 < 1700$ $S_4 \geq 2400$	2	Those confined to bed, needing assistance for most ADL, with mental functions not entirely compromised. Or, those with severe mental deficits but with no serious limitations in mobility and personal care functions.
8 9	$S_5 \geq 1200$ $S_6 \geq 800$	3	Those with no serious mental and mobility limitations, who need help several times a day for ADL (typically for hygiene and elimination tasks) while not requiring constant monitoring.
10 11	$S_7 \geq 650$ $S_8 \geq 4000$	4	Those who have transferring limitations, sometimes need help with washing and dressing, and most of them can eat without assistance. Or, those with no transferring limitations, but who need help to perform other ADL including eating.
12	$2000 \leq S_8 < 4000$	5	Those who can move around inside their home without assistance and can eat and dress themselves alone. They require occasional help with washing, preparing meals, and doing housework.
13	$S_8 < 2000$	6	Those who have not lost their autonomy for ADL

the persons who are completely dependent while the last group (GIR 6) represents autonomous persons. To identify a person's profile rank, the model uses 8 classification functions that compute the classification scores. The person is classified as belonging to the profile rank for which he/she has the highest classification score. Scores are tested in a sequential order using the defined classification functions: S_1 to S_8 (Table 3.3). Classification functions are defined as: $S_i = \sum_{k=1}^{8} w_{ik}$ where, S_i is the score of the i'th function; w_{ij} is the weight of the j'th variable modality which can be A, B, or C [8].

Table 3.4 presents the different weights of the variable modalities regarding the S_1 and S_2 functions. To simplify, let us consider an example of evaluation using this model. Let us consider a person with the following evaluation: *Coherence*=C, *Orientation*=C, *Hygiene*=C, *Dressing*=B, *Eating*=B, *Elimination*=B, *Transfers*=A, and *Interior Moving*=B. We have $S_1 = \sum_{k=1}^{8} w_{1k} = 3324$ and $S_2 = \sum_{k=1}^{8} w_{2k} = 2732$ (Table 3.4). To identify the profile rank, the score conditions are first tested with the S_1 score. If there is no satisfied condition, the score is then tested with the following function (i.e. S_2) and so forth until the last condition of S_8 ($S_8 < 2000$). Here, the score of S_1 (3324) does not satisfy the S_1 score conditions (Table 3.3). However, the score of S_2 (2732) satisfies the "$S_2 \geq 2016$" condition (Table 3.3). Hence, in our example, the person's profile rank is 4 and his iso-resource group (GIR) is 2 using Table 3.3.

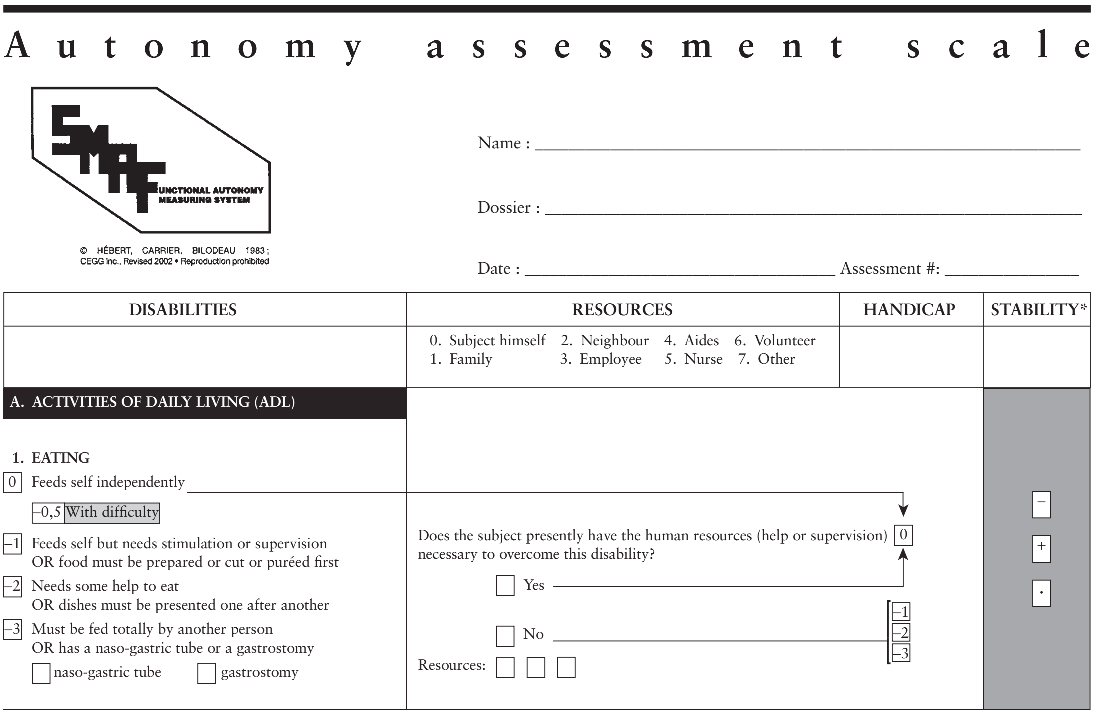
Table 3.4 – Weights of the classification functions S_1 and S_2 as defined in AGGIR

Activity		W_{1i}	W_{2i}	**Activity**		W_{1i}	W_{2i}
Coherence	C	2000	1500	Eating	C	60	60
	B	0	320		B	20	0
	A	0	0		A	0	0
Orientation	C	1200	1200	Elimination	C	100	100
	B	0	120		B	16	16
	A	0	0		A	0	0
Hygiene	C	40	40	Transferts	C	800	800
	B	16	16		B	120	120
	A	0	0		A	0	0
Dressing	C	40	40	Int. Moving	C	200	-80
	B	16	16		B	32	-40
	A	0	0		A	0	0

3.3.7 Functional Autonomy Measurement System

The Functional Autonomy Measurement System (SMAF) is a clinical rating scale used in Canada that measures the functional autonomy of elderly patients [269]. The SMAF is used to rehabilitate individuals by providing them appropriate care, services and assessing needs to alleviate the disabilities of elderly people [4][285]. Here, the handicap is the relation between disability and the available social or material resources, taken into account to alleviate the rate of disability. There are 29-items rating scale used to evaluates the person's dependency and access to available resources that may offset for the disabilities as well the stability of resources. These items are included in the following five aspects of functional abilities: activities of daily living (7 items), mobility (6 items), communication (3 items), mental functions (5 items), and IADL (8 items). Like AGGIR, the SMAF model is administrated manually by a health professional. The raters use all the available information to perform the rating. The dependency is evaluated by using a scale for each item with a 5-point rating scale: 0, -0.5, -1, -2, and -3. Items are evaluated using a function scoring with 0: independently, -0.5: independently but with difficulty, -1: needs supervision or stimulation, -2: needs help, and -3: dependent. Ten of the SMAF items are measured only using 4-point rating scale (i.e. 0, -1, -2, and -3) such as Urinary, Bowel, and Vision. The disability from autonomy to dependency is identified with a maximum negative score of -87. A higher disability score indicates a higher level of dependence. The handicap assessment is necessary to overcome the disability score. If the social resources are accessible to compensate the disability, the handicap score is zero; otherwise, the handicap score equals the disability score. Figure 3.1 shows a sample of the SMAF scale based on which the profile of the individual disabilities and handicaps is obtained.

SMAF has been developed in [271] to include 14 profiles of dependency patterns called *iso-SMAF* profiles. Based on the disabilities of groups, each profile is associated with a specific amount of nursing, support of services, supervision needed, and the costs of services. In SMAF, the first profile (profile 1) represents the persons who



Autonomy assessment scale

SMAF FUNCTIONAL AUTONOMY MEASURING SYSTEM

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Name :

Dossier :

Date : Assessment #:

DISABILITIES	RESOURCES	HANDICAP	STABILITY*
	0. Subject himself 2. Neighbour 4. Aides 6. Volunteer 1. Family 3. Employee 5. Nurse 7. Other		
A. ACTIVITIES OF DAILY LIVING (ADL) 1. EATING 0 Feeds self independently -0,5 With difficulty -1 Feeds self but needs stimulation or supervision OR food must be prepared or cut or puréed first -2 Needs some help to eat OR dishes must be presented one after another -3 Must be fed totally by another person OR has a naso-gastric tube or a gastrostomy naso-gastric tube gastrostomy	Does the subject presently have the human resources (help or supervision) necessary to overcome this disability? 0 Yes No -1 -2 -3 Resources:		- + ·

Figure 3.1 – Sample of SMAF autonomy assessment scale [4]

Table 3.5 – SMAF profiles, disability scores, and profiles classification

Number of Profiles	Disability score /87	Category	Number of Profiles	Disability score /87	Category
1	-9.33	1	8	-42.24	3
2	-13.23	1	9	-48.15	2
3	-19.76	1	10	-53.02	3
4	-23.69	2	11	-58.47	4
5	-28.54	3	12	-58.71	4
6	-32.04	2	13	-64.98	4
7	-39.19	3	14	-73.77	4

are autonomous while the last profile (i.e. profile 14) represents completely dependent persons. These profiles are determined based on the results of the information of all the 29 items. From the first to the last iso-SMAF profiles, the mean level of disability increases from 9.4 to 73.8 out of a potential of 87. The 14 iso-SMAF profiles are separated into 4 broad categories (1) mild mainly IADL disabilities: includes subjects who are autonomous with some IADL required supervision and help (with the profiles 1, 2, and 3) ; (2) intermediate predominantly motor disabilities: includes subjects who show mobility functions disabilities (with the profiles 4, 6, and 9) ; (3) intermediate predominantly mental disabilities: includes subjects who show mental disabilities (with the profiles 5, 7, 8, and 10) ; and (4) severe and mixed disabilities: shows the lowest level of autonomy (i.e. dependency) in all the ADL activities (with the profiles 11, 12, 13, and 14) [271][5]. Figure 3.2 describes each profile as it presented in [5]. Moreover, Table 3.5 briefly illustrates the association between profiles, disability scores, and the classification of iso-SMAF profiles.

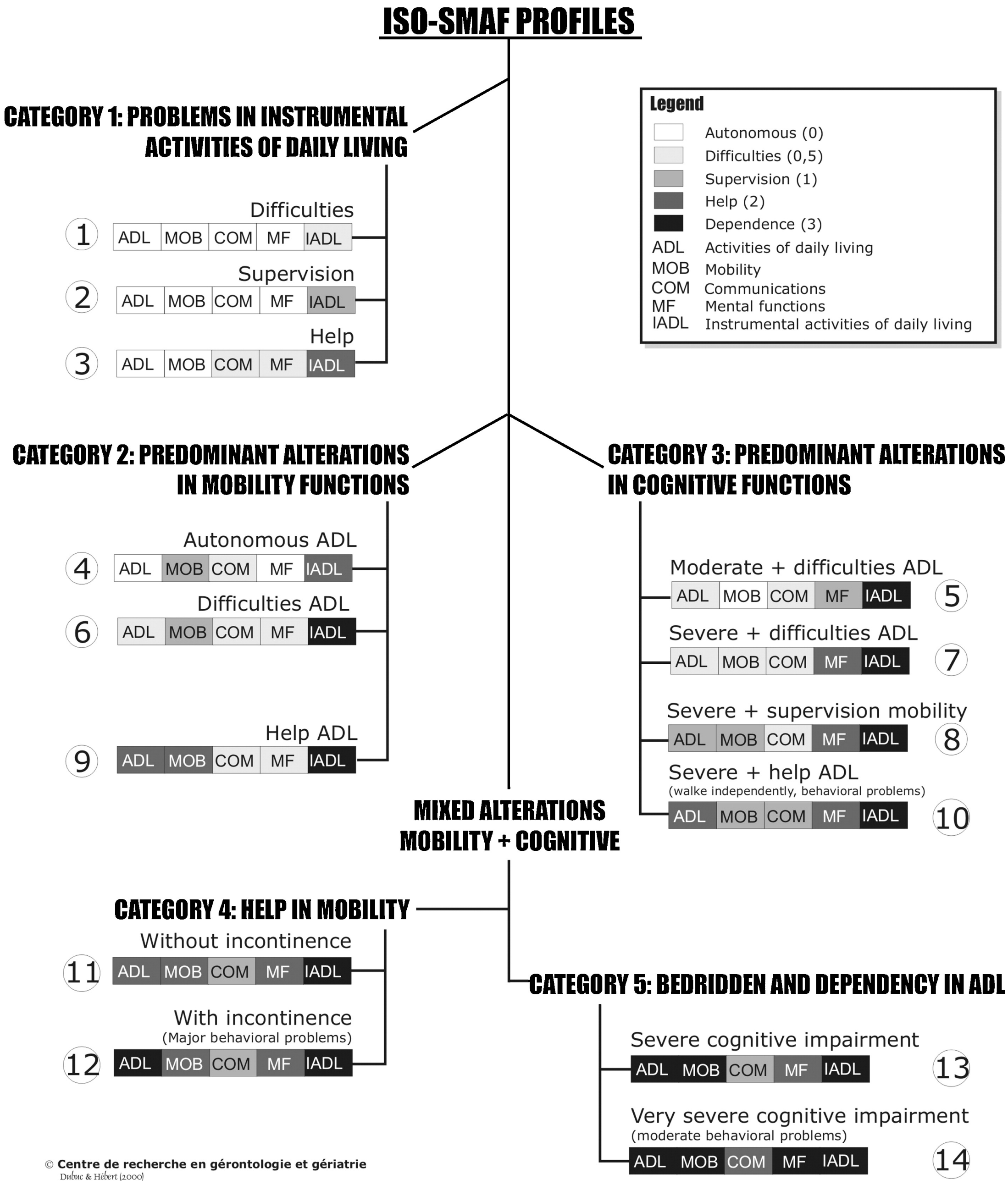

Figure 3.2 – Illustration of the 14 *iso-SMAF* profiles used in the SMAF model [5]

3.4 Activities Conceptualization in Smart Homes

A clear understanding of the elderly activities and their characteristics in the smart space is critical in order to proper and efficient sensing and framework design for the monitoring. An accurate knowledge of the activities' context, such as the interaction with objects, location, and time, enhances the effectiveness of the monitoring if it is incorporated into the activity conceptualization. In this section, we firstly describe a general taxonomy of the activities in a manner that can be meaningful for monitoring systems. Then, we present the characterization of the activities related to their conceptualization.

3.4.1 Taxonomy of Activities

In this sub-section, we present a taxonomy of activities that are often used in healthcare applications applied in a smart environment for the elderly and dependent persons. We include general information inspired from the geriatric models and existing health monitoring systems.

Functional abilities (i.e. ADL and IADL) related to the health status definition is a dominant area over others areas such as physical health, mental health, and social health. This is mainly due to the fact that the deterioration in other areas is reflected first by a loss of the functional abilities. Therefore, several works, related to the assisted living systems for elderly, were designed to handle the basic ADL activities as defined by Katz [267] such as eating, toileting, washing, etc. Other works focused on the detection of unclassified activities such as wash teeth and dishes while some studies targeted other important activities such sleeping which has never been considered in geriatric models.

Ambulatory activities (AMA) are activities that are related to the person's motion and posture. These activities can be divided into static, dynamic, and transition activities. Static activities describe a posture such as sitting, standing, and lying. The dynamic activities include a set of dynamic actions such as walking inside-outside and up-down, running, and jogging. Transitional activities refer to the changes of state from-to dynamic-static states (e.g. sit-to-stand, stand-to-sit, etc.). AMA are often used within motion tracking and fall detection systems. In addition, AMA can be useful in estimating the physiological activities and well-being of elderly. Authors in [286] proposed a health monitoring system for prolonged stress monitoring during normal activities performance in a smart home. They evaluated the individual momentary stress levels by analyzing both the ambulatory activities frequency and the heart rate when the person performs the ambulatory activities.

Mental functions (MF), such as memory and comprehension, are another type of important parameters that are used in health monitoring systems. This kind of functions is not achieved by the person like a classic action or activity but the system can deduce it based on the person's ability in performing other activities. For example, the person's ability to take medication in time can indicate memory.

The last important type in the monitoring community is related to physiological activities (PHA) such as the cardiac and brain activity. This type is usually used in a real time monitoring in order to retrieve the direct health parameters of elderly and patients especially those who suffer from chronic diseases.

The classification of the activities that are of high concern in healthcare and assisted living systems a smart environment are summarized in Table 3.6. This classification establishes the first step in defining the activities based on which sensors/network can be deployed in the smart space. This will guide the future adoption and identification of processing techniques that should be used to identify the context of the person.

3.4.2 Activity Conceptualization

Context-aware health monitoring applications which aim to detect the human behavior needs a clear description of the nature of human activities and their char-

Table 3.6 – Classification of the human activities

Type	Activities	Measurement methods and sensors
Activities of Daily Living (ADL)	Eating Drinking Dressing Washing Grooming Toileting Sleeping	appliance usage, PSN appliance usage, PSN PSN water usage, PSN water usage, PSN PSN PSN
Instrumental Activities of Daily Living (IADL)	Meal preparation Preparing drinks Housekeeping Laundry Telephone Medication use	appliance usage, PSN appliance usage, PSN appliance usage appliance usage appliance usage PSN
Ambulatory Activities (AMA)	Dynamic activities Stationary activities Transitional activities	BSN wearable inertial (sensors accelerometer/gyroscopes), PSN, video cameras
Mental Functions (MF)	Memory Comprehension Behaviour Social interaction Judgment Orientation	Deduced actions, user interactions, TV questionnaires (achieved by the person)
Physiological Activities (PHA)	Cardiac activity Brain activity Muscle activity	BSN wearable vital signs sensors (e.g. ECG and EEG)

acteristics. In a smart environment, there are many types of contextual information such as location, time, posture, frequency, and objects which can be critical during the monitoring. Such information can be used to characterize a given activity and to detect the human behavior [6, 7, 287].

Locations refer to specific places where a given activity is performed. For instance, taking a shower takes place in the bathroom. The activity time dimension, including the start-time and end-time (which can be replaced by duration), is another key characteristic for the description of an activity. For instance, sleeping at night is usually occurs in the evening and in a semi-regular timespan within normal daily routine. Objects are usually used in monitoring the human activities, where a given object can indicate the relevant activity. For example, using a broom indicates the housekeeping activity. Human postures are almost associated with the person's location and actions/activities that are being performed. Posture such as sitting and lying are used to characterize activities such as resting, waking, sleeping, etc. Also, in a normal life routine, some activities are performed with a known range of frequency (called also *repeatability*). For instance, taking a shower normally occurs once or twice a day. Finally, other contextual information can be used to detect the human activities such as temperature and humidity. All of these characteristics can be useful for monitoring and recognizing activities, detecting the human normal behavior and its abnormality, and to evaluate and predict the health status of the monitored person. Figure 3.3 shows the conceptual description of activities characterization in a smart environment.

Apart from the activity identifier (ID), name, and textual description, an activity can be described by a number of properties. These properties link an activity to other physical objects and conceptual entities. Some properties of time, location, and object (resources or actors) represent the context information within which the

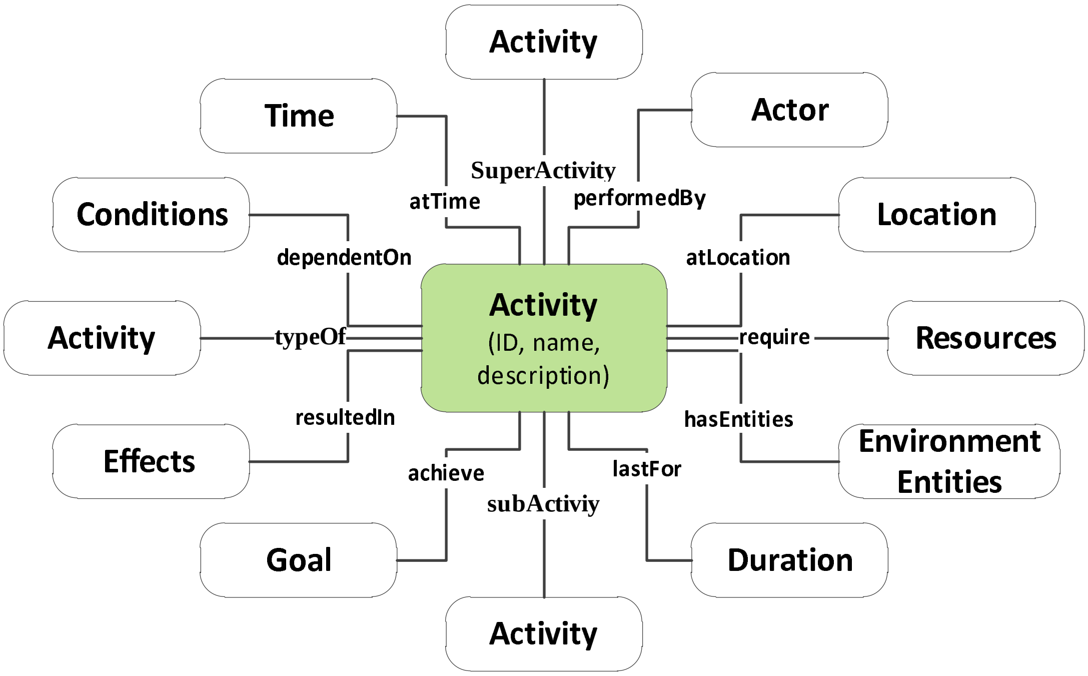

Figure 3.3 – Conceptual description of activities characterization [6]

activity takes place. Properties such as conditions and effects represent the causal and functional relations that are used for inference at the activity reasoning level. While *sub* and *super* classes properties refer to the type and interrelationship between activities [6].

Besides the contextual information for each activity, there are relationships between activities such as the interactions that could occur during the activity timespan. Activities can be categorized at multiple levels of granularity; simple activities (or actions) and composite activities [287]. The physical human behavior can be distinguished by either basic actions or activities. Actions and activities are used interchangeably to denote the human behavior at different complexity levels. On

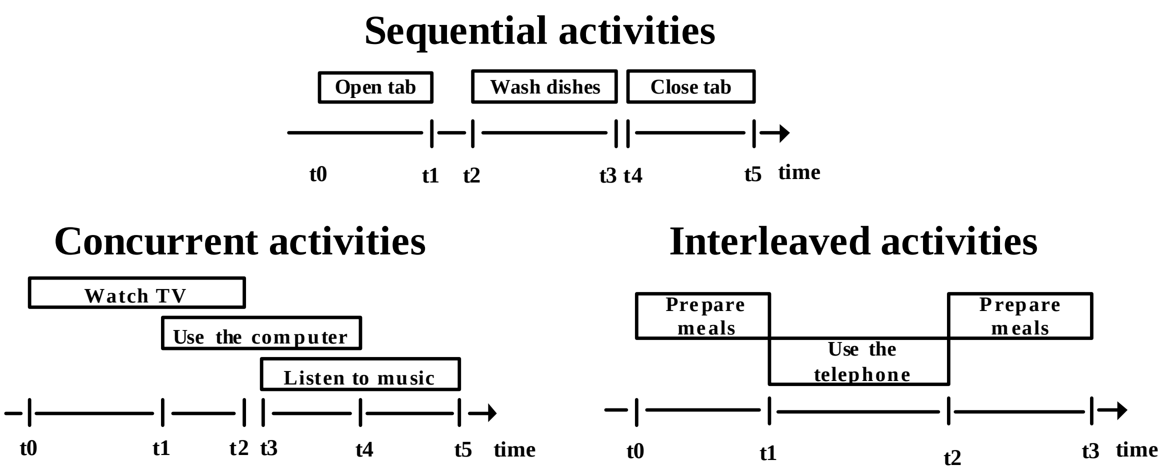

Figure 3.4 – Scenarios and relationships between activities [7]

one hand, an action is usually referred to a simple event that is executed by a single person and typically lasting for short time. For instance, opening a door, moving dishes, turn on light, etc. On the other hand, an activity usually refers to a more complex behavior consisting of a sequence of actions performed by either a single person or multiple persons who can interact with each other in a constrained manner. Of course, these activities, e.g. meal preparation, last for longer durations than actions. We note that in terms of time intervals, the so-called *Allen* relations [288], are commonly used to describe the temporal logic between activities [6, 7, 287]. Activities and their relations can be involved in three scenarios: sequential activities, concurrent activities, and interleaved activities. Here is an example of each scenario. Sequential activities with the *sleeping* including *open the door*, *lie on the bed*, and *turn light Off*; concurrent activities such as *watching TV* and *eating* simultaneously; and interleaved activities such as *meal preparation*, then *toileting*, and then *meal preparation*. Figure 3.4 shows graphically these temporal relationships as presented in [7].

3.5 Conclusion

In the systems of ambient assisted living (AAL) and activities of daily living (ADL) monitoring, the identification of the necessary activities to be monitored is of paramount importance. In most studies, the motivation behind the selection of the activities is not provided [9]. Moreover, current studies mostly address a limited scope of the ADL activities while others considered some events or a subset of activities (e.g. washing dishes, tooth brushing, etc.) as the main core in the monitoring of the person. In addition, modest attempts were noticed in addressing the instrumental activities (IADL). This situation is mainly due to that health applications and systems lacks a true understanding of the activities and their impact on the monitoring. Furthermore, we observed a notable limitation of adaptability in existing systems which leads to a narrow range of activities selection.

Part II

Contributions

CHAPTER 4

Elderly's Context and Dependency Models

Contents

4.1 Introduction

Dependency evaluation models are used to identify the needs of assistance and services for elderly in the geriatric domain. These models and medical knowledge can make a significant benefit in electronic health (e-health) services if they are properly adopted in the health monitoring system. The optimal use of this knowledge can contribute to the improvement of the context-awareness of e-health systems and facilitate their linking and integration with the real world and health institutions. The medical knowledge should be applied in health smart environments in order to confirm that the changes of behavior pattern, observed by the sensing system, are correlated with the health status of the monitored person. Most of the existing evaluation models used in the monitoring domain (e.g. AGGIR, SMAF, and FIM) are performed manually by clinical staff. We observe also that defined models consider, for the same purpose, different sets of daily activities. Consequently, they can lead to different dependency evaluations.

The objective that we target is to provide e-health services based on an automatic and homogeneous evaluation of the person's needs in terms of healthcare services. To do so, we believe that smart e-health platforms and systems have to gain a better understanding of the context of monitored persons. This will provide persons with context-aware services which are adapted, personalized and wich matche the person's required needs and assistance.

The contribution discussed in this Chapter can be seen as a step forward towards providing context-aware services for smart spaces and platforms such as at homes, cities, and health institutions. We consider the monitored person's context by studying and evaluating the existing tools used in the health domain. We focus on the needs in terms of healthcare services for dependent persons. We study the most famous models used in the geriatrics field to evaluate the person's dependency. We consider the AGGIR model, used in France, and the SMAF model used in Canada. We discuss the compatibility between the two models including the considered human's activities (items), the results and classification. We shed some light on the weakness of the existing dependency models in order to help to determine the improvement areas related to the consideration of the person's context and the focus on the main activities to be monitored.

The rest of this Chapter is structured as follows: in Section 4.2, an overview of the SMAF and AGGIR evaluations is presented. In Section 4.3, we discuss our methodology and propose matching mechanism between the experimented models. In Section 4.4, we propose a new algorithm that evaluates the person's activities based on the SMAF and AGGIR scales. Section 4.5, presents the experimentation and results of our geriatrics models evaluation. In Section 4.6, the outputs of our investigation are discussed. Finally, the conclusions of this Chapter are drawn in Section 4.7.

4.2 Generalities

In the context of e-health services and smart home (or city) environments, the determination of the relevant daily activities that directly affect the lives of the elderly is of high concern. It is the essence and basis of automatic evaluation and monitoring. A continuous monitoring of these identified activities helps to reveal the person's real needs and allows an immediate providing of required assistance and services, especially for dependent persons. As stated before, the motivation behind the selection of the monitored activities in existing health system was not provided. This selection/identification step is still challenging and needs more efforts. In this Chapter, we study the overlaps and differences between the most important models used to evaluate the dependency of monitored persons.

Recall that the existing geriatrics models have different methods to calculate the dependency level of a given person. We observed that the concept of person's *profile* and *group* is used in these models in order to classify the persons based on their needs, assistance, costs, diagnosis, etc. The SMAF model has 29 items which are included in five aspects of functional abilities. The abilities are ADL, mobility, communication, mental functions, and IADL. Each item is given a score of 0, -0.5, -1, -2, or -3. There are 16 items measured by this 5-point rating scale, while 10 items are measured only using a 4-point rating scale (i.e. 0, -1, -2, and -3). The person's disability, varying from autonomy to dependency, is identified with a maximum negative score of -87. A higher disability score denotes a higher level of dependence, thus, the amount of person's need for care is increased.

The SMAF model defines 14 profiles of dependency patterns called *iso-SMAF* profiles. Each profile is associated with a specific amount of help (nursing, support

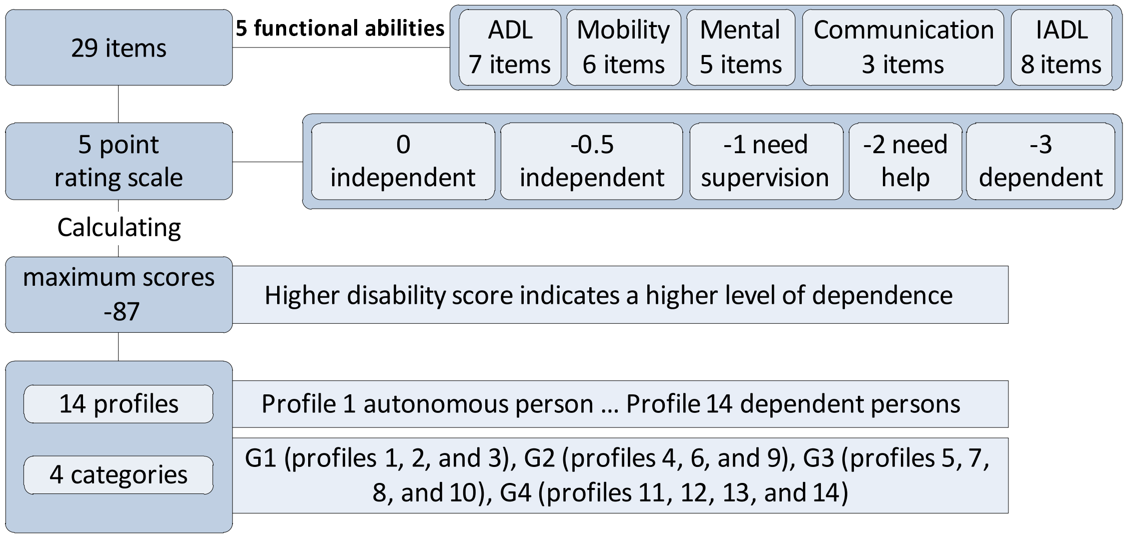

Figure 4.1 – SMAF items, profiles, and evaluation

services, supervision, and costs of required services) based on the disabilities of the group to which the evaluated person belongs. The first profile (profile 1) gathers the persons that are autonomous while the last profile (profile 14) represents completely dependent persons. The profiles have been separated into 4 broad categories: mild mainly IADL disabilities (profiles 1, 2, and 3), intermediate predominantly motor disabilities (profiles 4, 6, and 9), intermediate predominantly mental disabilities (profiles 5, 7, 8, and 10), and severe and mixed disabilities (profiles 11, 12, 13, and 14), see Chapter 3. Figure 4.1 presents SMAF items and profiles evaluation.

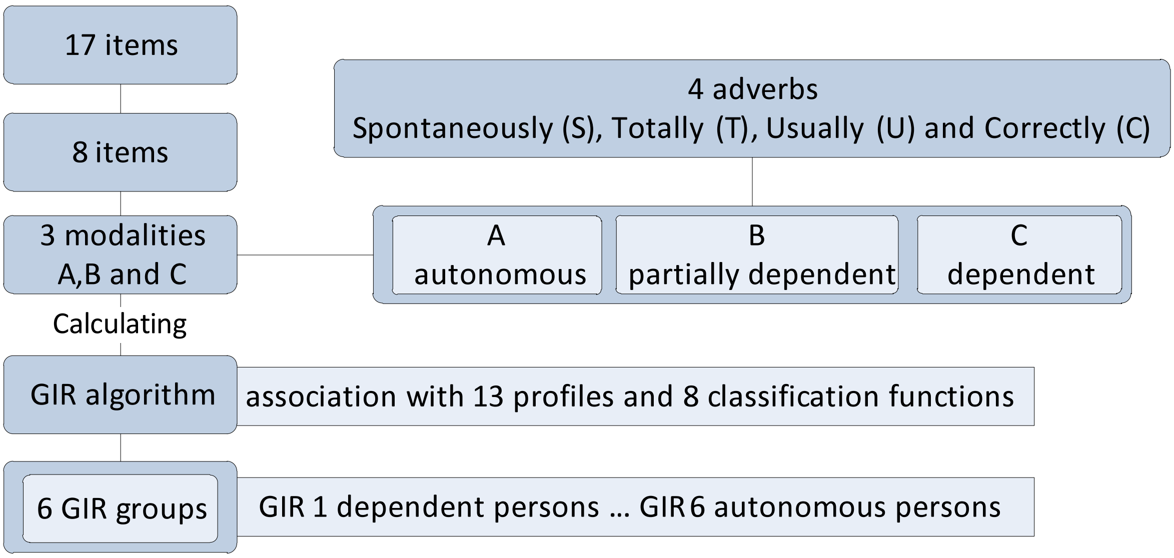

Figure 4.2 – AGGIR items, groups, and evaluation

The AGGIR model considers 17 items describing the activities of daily living. Eight of them are really used in the classification of the dependent persons, which in turn creates 13 profile ranks and 6 groups. Each considered item is qualified by the medical reviewer using the four possible adverbs: *Spontaneously* (S), *Complete-*

Table 4.1 – Activities and items evaluation using the SMAF and AGGIR methods

Act.	SMAF	AGGIR	AGGIR Modalities	SMAF Scores
ADL	1. Eating	1. Eating	3 (A, B and C)	5 (0, -0.5, -1, -2, -3)
	2. Dressing	2. Dressing	3 (A, B and C)	5 (0, -0.5, -1, -2, -3)
	3. Washing	3. Hygiene	3 (A, B and C)	5 (0, -0.5, -1, -2, -3)
	4. Grooming			5 (0, -0.5, -1, -2, -3)
	5. Urinary function	4. Elimination	3 (A, B and C)	4 (0, -1, -2, -3)
	6. Bowel function			4 (0 ,-1, -2, -3)
	7. Toileting			5 (0, -0.5, -1, -2, -3)
Mobility	1. Transfers	1. Transfers	3 (A, B and C)	5 (0, -0.5, -1, -2, -3)
	2. Walking inside	2. Internal Moving	3 (A, B and C)	5 (0, -0.5, -1, -2, -3)
	3. Walking outside			5 (0, -0.5, -1, -2, -3)
	4. Donning prosthesis or orthotic			5 (0, -0.5, -1, -2, -3)
	5. Propelling a wheelchair			5 (0, -0.5, -1, -2, -3)
	6. Negotiating stairs			5 (0, -0.5, -1, -2, -3)
Com.	1. Vision			4 (0, -1, -2, -3)
	2. Hearing			4 (0, -1, -2, -3)
	3. Speaking	1. Coherence	3 (A, B and C)	4 (0, -1, -2, -3)
Mental Function	1. Behavior			4 (0, -1, -2, -3)
	2. Judgment			4 (0, -1, -2, -3)
	3. Orientation	2. Orientation	3 (A, B and C)	4 (0, -1, -2, -3)
	4. Memory			4 (0, -1, -2, -3)
	5. Comprehension			4 (0, -1, -2, -3)
IADL	1. Housekeeping			5 (0, -0.5, -1, -2, -3)
	2. Meal preparation			5 (0, -0.5, -1, -2, -3)
	3. Shopping			5 (0, -0.5, -1, -2, -3)
	4. Laundry			5 (0, -0.5, -1, -2, -3)
	5. Telephone			5 (0, -0.5, -1, -2, -3)
	6. Transportation			5 (0, -0.5, -1, -2, -3)
	7. Medication use			5 (0, -0.5, -1, -2, -3)
	8. Budgeting			5 (0, -0.5, -1, -2, -3)

ly/Totally (T), *Usually* (U) and *Correctly* (C). According to the logical conditions involving these adverbs, a given activity is evaluated with one of the following modalities: A, B or C. The A evaluation is given if the person is completely autonomous in achieving the evaluated activity, B is given if the person is partially dependent and C is used if the person is dependent and can not achieve the activity alone.

The 13 profile ranks refer to a decline in autonomy of persons. The 6 groups, called *iso-resource* groups (GIR), reduce the number of profiles and address the common needs of assistance. The GIR 1 represents the group of persons who are completely dependent while the last group (GIR 6) represents autonomous persons. The evaluation method (called GIR algorithm) computes the GIR number (1 to 6) based on a predefined association between the profile ranks and the groups. Figure 4.2 shows the general information included in the AGGIR model. More details about the GIR algorithm, classification functions, and the identification of profiles and ranks can be found in Chapter 3 with a detailed example. Table 4.1 shows the evaluation of activities using the SMAF scores and the AGGIR modalities.

4.3 Methodology

In order to improve the knowledge about the context of monitored persons, we focus on the evaluation of the human activities that will be monitored using e-health systems. The evaluation of the human activities helps to determine the dependency level of the person and hence, allows the system to provide automatic e-health services and care accordingly. We were interested in studying how the person's context can be handled and evaluated in the existing models defined in the geriatrics domain. To reach this goal, we perform a set of simulations regarding all the possible categories of persons (i.e. dependency scenarios) and apply the SMAF and AGGIR models to evaluate them.

In our simulation, a huge amount of data is handled which come from twenty trillion (5^{19}x4^{10}) of possible evaluations in SMAF and more than six thousand (3^8) of possible evaluations in AGGIR. Each processed evaluation represents a person with a certain ability (i.e. situation of dependency). A given situation is represented by values (i.e. rating scale) associated with all the items defined in the used model. In order to be able to evaluate the same person with different models using our simulations, we perform a matching and aggregation between the SMAF and AGGIR items. Aggregated items are those referring to similar activities. To do so, we have identified thirteen (13) items defined in SMAF and all the items (8) defined in the AGGIR model. Figure 4.3 shows an example of this matching.

In our proposed matching strategy, we associate either one item of the SMAF model with one item of the AGGIR model (i.e. *one-to-one* association) or several items of SMAF with one item of AGGIR (i.e. *many-to-one* association). For instance, in the one-to-one association, the *eating* item of the SMAF model, with scoring criteria varying from -3 to 0, corresponds with the *eating* activity of AGGIR with the scoring criteria of *A, B* or *C*. For the second type of association (i.e. many-to-one), we perform the matching between the SMAF and AGGIR items by using a specific a weight which is based on the priority for each item. For instance, in the matching of the AGGIR's *hygiene* item (H), we associate the *washing* item with a 0.70 ratio of priority and the *grooming* item with a 0.30 ratio of priority. Consequently, we have $H = 0.7.Washing + 0.3.Grooming$ (see Figure 4.3 and Table 4.2).

The choice of these weights is explained by the observation that only some part of *grooming*'s properties cares about cleaning in SMAF. In addition, as explained previously, the SMAF scoring of 0 refers to a full autonomy while -0.5 refers to autonomy with minor difficulties. Consequently, in our matching strategy, we associate

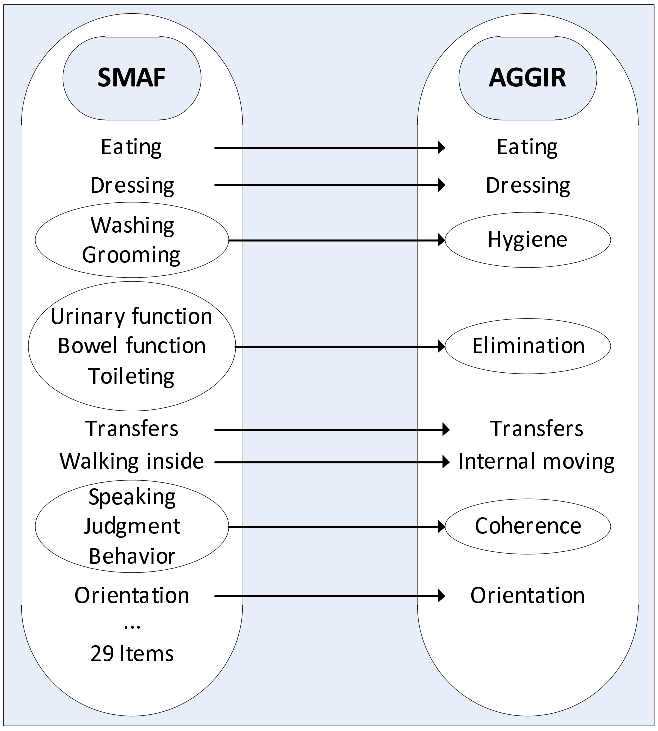

Figure 4.3 – Proposed matching of items between dependency models

0 and -0.5 with the *A* scoring of AGGIR. The SMAF scoring of -1 and -2 indicate an increased level of dependency so we associate it with the *B* evaluation in the AGGIR model. Finally, the maximum level of dependency is evaluated with -3 in SMAF and, hence, with *C* in AGGIR. Table 4.2 illustrates our items matching between SMAF and AGGIR. It is worth noting that in the simple matching association (i.e. one-to-one) we use the following associations: -3 $\rightarrow$ C, -2 $\rightarrow$ B, -1 $\rightarrow$ B, -0.5 $\rightarrow$ A, and 0 $\rightarrow$ A. For the many-to-one matching, we use the following associations: [-3 ,-2[$\rightarrow$ C, [-2 ,-1] $\rightarrow$ B, and]-1 , 0] $\rightarrow$ A.

4.4 Proposed Algorithm

In this section, we propose a new algorithm (Algorithm 1) that evaluates all the different context instances related to the different persons' activities (i.e. ADL and IADL). We consider the 29 activities (that we call SM_1 to SM_{29}), presented in Table 4.1, with different dependency evaluations using either the SMAF or the AGGIR evaluation method. The matching method discussed previously, was implemented using the *Smaf2Aggir* matching function. The function uses the different associations between the SMAF scores and the AGGIR evaluations presented in Table 4.2.

We compute the SMAF profiles using the (*GetSMAFprofile*) function, match 13 items from SMAF to all the 8 items (A_1 to A_8) used in AGGIR, and then compute the AGGIR scores (*AggirScor*). Our algorithm returns the M matrix that gives the distribution of all the dependency evaluations using SMAF and AGGIR. Indeed, after each simulation's instance (see the inner loops), the M matrix counts and

Table 4.2 – Proposed matching between items and between the models evaluations

<table>
<tr><th>Act.</th><th>SMAF Items</th><th>AGGIR Items</th><th>Matching between the SMAF evaluation and the AGGIR evaluation of items</th></tr>
<tr><td rowspan="7">ADL</td><td>Eating</td><td>Eating</td><td>Eating → Eating:
0 → A, -0.5 → A, -1 → B, -2 → B, -3 → C</td></tr>
<tr><td>Dressing</td><td>Dressing</td><td>Dressing → Dressing:
0 → A, -0.5 → A, -1 → B, -2 → B, -3 → C</td></tr>
<tr><td>Washing</td><td rowspan="2">Hygiene</td><td rowspan="2">(Washing ∈ {0, -0.5, -1, -2, -3}, Grooming ∈ {0, -0.5, -1, -2, -3}) → Hygiene ∈ {A, B, C}:
H = 0.7.Washing + 0.3.Grooming
H ∈ [-3 ,-2[→ Hygiene = C
H ∈ [-2 ,-1] → Hygiene = B
H ∈]-1 , 0] → Hygiene = A</td></tr>
<tr><td>Grooming</td></tr>
<tr><td>Urinary function</td><td rowspan="3">Elimination</td><td rowspan="3">(Urinary ∈ {0, -1, -2, -3}, Bowel ∈ {0, -1, -2,-3}, Toileting ∈ {0, -0.5, -1, -2,-3})
→ Elimination ∈ {A, B, C}:
E = 0.4. Urinary + 0.4. Bowel + 0.2. Toileting
E ∈ [-3 ,-2[→ Elimination = C
E ∈ [-2 ,-1] → Elimination = B
E ∈]-1 , 0] → Elimination = A</td></tr>
<tr><td>Bowel function</td></tr>
<tr><td>Toileting</td></tr>
<tr><td rowspan="2">Mobility</td><td>Transfers</td><td>Transfers</td><td>Transfers → Transfers:
0 → A, -0.5 → A, -1 → B, -2 → B, -3 → C</td></tr>
<tr><td>Walking inside</td><td>Internal Moving</td><td>Walking inside → Internal Moving
0 → A, -0.5 → A, -1 → B, -2 → B, -3 → C</td></tr>
<tr><td>Com.</td><td>Speaking</td><td rowspan="3">Coherence</td><td rowspan="3">(Behavior ∈ {0, -1, -2, -3}, Judgment ∈ {0, -1, -2,-3}, Speaking ∈ {0, -1, -2,-3}) → Coherence ∈ {A, B, C}:
C = 0.5. Behavior + 0.3. Judgment + 0.2. Speaking
C ∈ [-3 ,-2[→ Coherence = C
C ∈ [-2 ,-1] → Coherence = B
C ∈]-1 , 0] → Coherence = A</td></tr>
<tr><td rowspan="3">Mental Functions</td><td>Behavior</td></tr>
<tr><td>Judgment</td></tr>
<tr><td>Orientation</td><td>Orientation</td><td>Orientation → Orientation
0 → A, -0.5 → A, -1 → B, -2 → B, -3 → C</td></tr>
</table>

save the instance into the right index of M (i.e. M *[SMAF-Profile, GIR]* $\leftarrow$ M *[SMAF-Profile, GIR]* $+ \delta$ with $\delta = 1$).

4.5 Experimentation and Results

The execution time of the Algorithm 1, as presented previously, takes a very long time. Indeed, for the simulation of only one million of dependency situations, the running time is approximately 2.66 seconds under a DELL Precision M6700 computer with an Intel® Core^{TM} i7-3940XM, 3.20 GHz processor and 32 GB of RAM. Consequentlly, the Algorithm 1 will require approximately 1.687.826 years

Algorithm 1 SMAF and AGGIR evaluations with all the possible situations

```
for SM1 ← 1 to 5 do
    ...
    //note that some of the SM variables vary from 1 to 4 and not 1 to 5
    ...
    for SM29 ← 1 to 5 do
        Smafscore ← SM1 + SM2 + ... + SM29
        SMAF_Profile ← GetSMAFprofile (Smafscore)
        GIR ← AggirScor (Smaf2AggirMatching(SM1, SM2, .. , SM29))
        M [SMAF_Profile, GIR] ← M [SMAF_Profile, GIR] + δ
    end for
end for
function AggirScore(A1, A2, .. , A8)
    compute the AGGIR scores S1, S2, .. , S8
    if S1 ≥ 4380 then
        return 1
    else if (S1 ≥ 4140 and S1 < 4380) or (S1 ≥ 3390 and S1 < 4140) or .. or (S4 ≥ 2400) then
        return 2
    else if ... then (see Chapter 3 & Table 3.3)
    end if
end function
function GetSMAFprofile(Smafscore)
    if Smafscore ≤ -9.33 and Smafscore > -13.23 then
        return 1
    else if Smafscore ≤ -13.23 and Smafscore > -19.76 then
        return 2
    else if ... then (see Chapter 3 Table 3.5)
    end if
end function
```

for the complete simulation which means with the twenty trillion of situations. In order to reduce the execution time required for performing all the simulations, we split the twenty-nine loops of the algorithm and identify two independent parts that can be executed separatly. This identification has lead us to define two new algorithms.

The first part (Algorithm 2) computes all of the possible scores of SMAF with the variables used only in SMAF and never in AGGIR. There are 16 variables (items) used only in SMAF where 12 variables can be evaluated with 5 possible scores (0, -0.5, -1, -2, or -3) and 4 variables can be evaluated with 4 possible scores (0, -1, -2, or -3). The variation of simulated situations invloving these 16 variables implies a number of $625x10^8$ possible scores (i.e. $5^{12}x4^4$) that can not affect the AGGIR evaluation. As defined in the SMAF model, each item is given a score from 0 to -3 with possibile step of -0.5. Consequentlly, if all the 16 items are evaluated with a score of 0 then the final score will be 0 since SMAF applies a summation of item scores. If only one item is given a score of -0.5, then the final score will be -0.5. There are only 12 possibilities to obtain this total score of -0.5 since there are only 12 items which can be evaluated with -0.5. From this, it becomes obvious that the maximum negative score of these 16 variables is -48 (i.e. $-3 * 16$). Table 4.3 presents a subset of the possible scores with the identifies 16 items of SMAF. Specifically, the table shows the possible *different* scores (varying from 1 to 97) where each row includes the order number of the different score, the score value and the number of possible situations that can be evaluated with the given score value. The results of this first part, defined by Algorithm 2, will be used in the second part defined in Algorithm 3.

Table 4.3 – Possible scores with the SMAF variables that do not affect the AGGIR evaluation

Order number	Score value	Number of possibilities situations
1	0	1
2	-0.5	12
3	-1	82
4	-1.5	400
...	...	...
44	-21.5	2833983052
45	-22	2816014058
46	-22.5	2753769408
47	-23	2670267398
...	...	...
97	-48	1

Algorithm 2 Possible scores with the SMAF-only variables

```
for SM1 ← 1 to 5 do
    ...
    //note that some of the SM variables vary from 1 to 4 and not 1 to 5
    ...
    for SM16 ← 1 to 5 do
        PossibleScore ← SM1 + SM2 + ... + SM16
        M [-2 * PossibleScore] ← M [-2 * PossibleScore] + 1
        //note that the use of "-2" is only to obtain a positive integer index since
        //the values of PossibleScore can be 0, -0.5, .., -48, see Table 4.3
    end for
end for
```

The second part of our new algorithm (Algorithm 3) computes the SMAF and AGGIR evaluations with the thirteen (13) remaining variables (items) used in both of SMAF and AGGIR evaluations (see Table 4.2). These 13 variables lead to a number of possible evaluations of 32.10^7 where, in SMAF, 7 variables of them have 5 possible scores while the 6 other variables have 4 possible scores ($5^7.4^6$ possible

SMAF evaluations). In Algorithm 3, after the calculation of the SMAF score for the 13 items (using the *SmafscoreTemporary* variable), the final SMAF scores is computed by applying the summation of *SmafscoreTemporary* and the different possible scores (using the *PossibleScore* values) coming from Algorithm 2). To properly understand the algorithm, it is important to note that the values of *PossibleScore* are varying from 0 to -48 with a step of -0.5 (as presented in Table 4.3) and the matrix M of Algorithm 2 saves the number of occurrences, that we call δ, of each different possible score.

In Algorithm 3, we calculate the SMAF profile, using the *GetSMAFprofile* function (see Algorithm 1), and the GIR group, using the *AggirScore* function (see Algorithm 1) with our matching method *Smaf2AggirMatching* as presented in Table 4.2. In Line 10 (Algorithm 3), the M matrix incrementally counts the instances of SMAF and AGGIR evaluations (using the element *M[SMAF_Profile, GIR]*) for each same situation (i.e. each combination of items evaluations) without forgetting the δ value, coming from Algorithm 2 (see Table 4.3). Recall that δ represents the number of situations that do not affect the SMAF and AGGIR evaluation of the situation being processed in the main loop of Algorithm 3.

The running time of the first part (Algorithm 2) was 1.35 hours (under the previous simulation conditions) while the running time of the second part (Algorithm 3) was 3.81 hours.

Algorithm 3 Optimized version of the SMAF and AGGIR evaluations of all the possible situations

1: **for** $SM1 \leftarrow 1$ to 5 **do**
2:     ...
3:     *//note that some of the SM variables vary from 1 to 4 and not 1 to 5*
4:     ...
5:     **for** $SM13 \leftarrow 1$ to 5 **do**
6:         *SmafscoreTemporary* $\leftarrow SM1 + SM2 + ... + SM13$
7:         *Smafscore* = *SmafscoreTemporary* + *PossibleScore*
8:         *SMAF_Profile* $\leftarrow$ GetSMAFprofile (*Smafscore*)
9:         GIR $\leftarrow$ AggirScor (Smaf2AggirMatching($SM1$, $SM2$, .. , $SM13$))
10:         M [*SMAF_Profile*, GIR] $\leftarrow$ M [*SMAF_Profile*, GIR] + δ
11:     **end for**
12: **end for**

It is important to notice that the authors in [289] studied and compared the classification of persons' dependency using the two models AGGIR and SMAF. Their experimentations were done with a limited group of 207 persons. Unlike [289], we perform the simulation of AGGIR and SMAF evaluations over all the possible dependency situations of people. We consider the evaluation scores for all the activities (items) used in both of SMAF and AGGIR models and achieve a complete correspondence between them. Table 4.4 shows the matching between the SMAF and AGGIR evaluations in terms of *iso-SMAF* profiles and AGGIR groups by applying our simulation (see our methodology in Section 4.3). The results are presented using the M matrix used in Algorithm 3 in the form of percentages. While, Figure 4.4 shows the distribution of GIR within the SMAF profiles. We have performed an analysis of the characteristics of profiles in SMAF and GIR groups, including the classification of the person's dependency.

Table 4.4 – Matching and distribution percentages between the SMAF and AGGIR evaluations

SMAF category & profile \ AGGIR group & profile		GIR_1	GIR_2	GIR_3	GIR_4	GIR_5	GIR_6
		P_{a1}	$P_{a2,3,4,5,6,7}$	$P_{a8,9}$	$P_{a10,11}$	P_{a12}	P_{a13}
C_1	$\mathbf{P}_{s1}$	0	0.029	0.166	19.561	43.300	36.943
	$\mathbf{P}_{s2}$	0	0.653	3.047	40.587	38.199	17.514
	$\mathbf{P}_{s3}$	0	2.097	8.511	49.341	30.064	9.987
C_2	$\mathbf{P}_{s4}$	1.10^{-10}	5.650	18.482	51.089	19.957	4.822
C_3	$\mathbf{P}_{s5}$	6.10^{-8}	10.279	27.651	46.772	12.879	2.419
C_2	$\mathbf{P}_{s6}$	3.10^{-5}	20.152	38.518	34.559	5.949	0.821
C_3	$\mathbf{P}_{s7}$	4.10^{-4}	30.446	43.709	23.124	2.476	0.244
	$\mathbf{P}_{s8}$	0.004	40.882	43.628	14.359	1.047	0.079
C_2	$\mathbf{P}_{s9}$	0.039	54.883	38.677	6.147	0.242	0.012
C_3	$\mathbf{P}_{s10}$	0.208	66.556	30.939	2.248	0.048	0.001
C_4	$\mathbf{P}_{s11}$	0.579	74.301	24.302	0.809	0.009	2.10^{-4}
	$\mathbf{P}_{s12}$	0.985	77.326	21.192	0.493	0.005	6.10^{-5}
	$\mathbf{P}_{s13}$	3.883	84.155	11.916	0.045	1.10^{-4}	3.10^{-7}
	$\mathbf{P}_{s14}$	19.407	77.515	3.078	2.10^{-5}	0	0

In the following, P_1, P_2,. . . , P_{14} refer to the iso-profile 1, iso-profile 2, . . . , iso-profile 14 as defined in the SMAF model. For the AGGIR model, GIR_1, GIR_2,. . . , GIR_6 refer to the group number which denotes the level of dependency.

The first observation on the obtained results is related to the full autonomy of persons. We can observe that the profile P_1 of SMAF shows a high matching with the GIR_5 of AGGIR. P_1 matches GIR_5 with 43.3% and matches GIR_6 with 36.9%. This matching was unexpected based on the results of [289]. A deep study of the two models enables us to explain this situation. Indeed, the SMAF profile P_1 refers to the person's autonomy but with additional services related to supervision and help (e.g., housekeeping, heavy housework, and meal preparation). However, the GIR_6 refers only to strong autonomy. Therefore, the highest percentage of people, who belong to profile P_1, have to be classified into the GIR_5 more than in the GIR_6. We notice, that the researchers in [289] obtained a perfect match (100%) between P_1 and GIR_6, probably due to the small sample used (only 207 subjects).

The second observation is similar to the previous one but is related to the full dependency of persons. For the full dependency level, P_{14} of SMAF did not appear with a high level of matching with GIR_1 (only 19.4% of matching). Indeed,

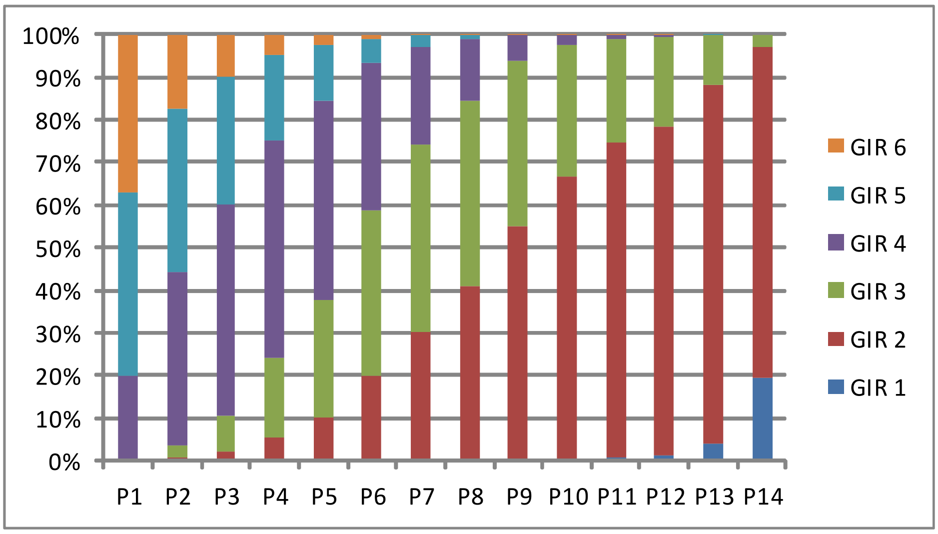

Figure 4.4 – Distribution of AGGIR groups (GIR) within the SMAF profiles

the highest matching of P_{14} is observed with GIR_2 (77.5% matching). The same situation is observed for P_{11}, P_{12} and P_{13} where their high matching is observed with GIR_2 rather than GIR_1.

The third observation is related to the SMAF categories (see Section 4.2). We recall that the profiles P_1, P_2 and P_3 (i.e. the category 1 of SMAF) are related to autonomy with some needs of assistance and help like in the AGGIR model with the GIR_5 and GIR_6 groups. Figure 4.4 shows that only some percentage of the SMAF category 1 is represented by the GIR_5 and GIR_6. This percentage is exactly equaled to

$$\sum_{i=1}^{3}\sum_{j=5}^{6} M[P_i, GIR_j] / \sum_{i=1}^{3}\sum_{j=1}^{6} M[P_i, GIR_j] = 41.182\%.$$

The fourth observation is related to the dependency level of persons described by the category 4 in SMAF (Section 4.2) and the GIR_1 group in AGGIR. Only a very few percentage of the category 4 is represented by the GIR_1:

$$\sum_{i=11}^{14} M[P_i, GIR_1] / \sum_{i=11}^{14}\sum_{j=1}^{6} M[P_i, GIR_j] = 0.916\%.$$

We notice that the remaining situations (i.e. excluding high levels of autonomy and dependency) are related to motor and mental disabilities (i.e. categories 2 and 3 of SMAF) which correspond to the AGGIR groups from GIR_2 to GIR_4 as presented in Table 4.4.

Our simulation of all the possible dependency situations (i.e. $2\text{x}10^{19}$ situations) has revealed some incoherence between the studied models in their evaluation of the required needs and assistance. First, we observe that some persons who are considered in a strong dependency in SMAF with category 4 (i.e. P_{11}, P_{12}, P_{13}, and P_{14}) have not been classified with the dedicated group in AGGIR (i.e. GIR_1).

Consequently, these persons are not receiving their real required needs since they were classified in groups GIR_2 to GIR_6. This percentage is exactly equaled to

$$\sum_{i=11}^{14}\sum_{j=2}^{6} M[P_i, GIR_j]/2.10^{19} = 0.086\%.$$

Similarly, some persons starting to have a decline in their autonomy (i.e. classified from P_4 to P_{14} in SMAF) were considered in the AGGIR model as autonomous persons (i.e. GIR_1) hence they will not receive any assistance. The exact amount of this category equals to

$$\sum_{i=4}^{14} M[P_i, GIR_6]/2.10^{19} = 0.679\%.$$

Moreover, persons with high levels of autonomy classified with SMAF in category 1 (i.e. P_1, P_2 and P_3) were distributed into the AGGIR's dependency levels from GIR_1 to GIR_4. Thus, they will receive services and assistance more than their real needs. The exact amount of this category of persons is

$$\sum_{i=1}^{3}\sum_{j=1}^{4} M[P_i, GIR_j]/2.10^{19} = 0.152\%.$$

Figure 4.5 presents the overall percentages of matching between SMAF categories and GIR groups while Figure 4.5 shows the the distribution of GIR groups with the SMAF categories.

Table 4.5 – Matching between SMAF categories and GIR groups

	$\mathbf{GIR_1}$	$\mathbf{GIR\ _2}$	$\mathbf{GIR_3}$	$\mathbf{GIR_4}$	$\mathbf{GIR_5}$	$\mathbf{GIR_6}$
$\mathbf{C_1}$	0%	1.99%	8.12%	48.71%	30.65%	10.53%
$\mathbf{C_2}$	0.01%	24.06%	37.36%	31.64%	5.99%	0.94%
$\mathbf{C_3}$	0.01%	33.41%	41.25%	21.73%	3.15%	0.46%
$\mathbf{C_4}$	0.92%	76.64%	21.87%	0.57%	0.01%	0%

Our simulation has processed all of the $2x10^{19}$ possible dependency situations. These situations (or context instances) were obtained by varying the person's ability, and hence its evaluation, in performing each activity of daily living (Algorithm 1). The consideration of all context instances has allowed us to compare the considered amount of autonomous/dependent persons between SMAF and AGGIR. The number of persons considered as autonomous in SMAF ($A_s = 0.258\%$) is less than this number in AGGIR ($A_g = 5.235\%$) while the number of dependent persons in SMAF ($D_s = 0.087\%$) is more than this number in AGGIR ($D_g = 0.007\%$). Indeed, regarding the autonomy in the SMAF model (i.e. category 1), we have

$$A_s = \sum_{i=1}^{3}\sum_{j=1}^{6} M[P_i, GIR_j]/2.10^{19} = 0.258\%,$$

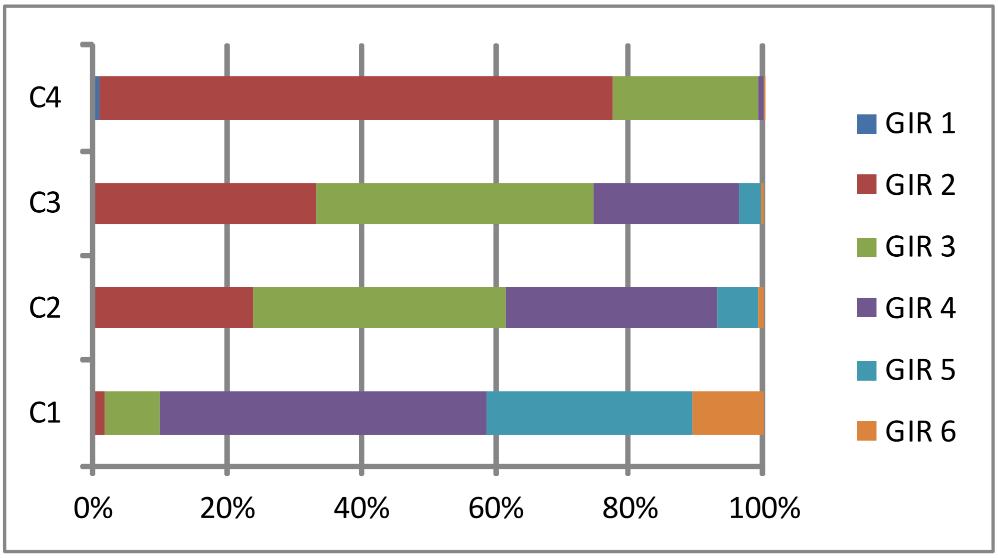

Figure 4.5 – Distribution of AGGIR groups (GIR) within the SMAF categories

while for the autonomy considered in AGGIR (i.e. GIR_5 and GIR_6), we have

$$A_g = \sum_{i=1}^{14} \sum_{j=5}^{6} M[P_i, GIR_j]/2.10^{19} = 5.235\%.$$

For persons dependency (i.e. category 4 in SMAF), we have in

$$D_s = \sum_{i=11}^{14} \sum_{j=1}^{6} M[P_i, GIR_j]/2.10^{19} = 0.087\%,$$

while in AGGIR (i.e. with GIR_1), we have

$$D_g = \sum_{i=1}^{14} M[P_i, GIR_1]/2.10^{19} = 0.007\%,$$

It is noteworthy that in the SMAF model, a given subject has a high probability to be classified in the profile P_6 which is related to persons who need assistance mainly in their mobility activities. This probability is

$$\sum_{j=1}^{6} M[P_6, GIR_j]/2.10^{19} = 37\%.$$

In AGGIR, the highest probability concerns the group GIR_3 which refers to persons who need assistance mainly in mental activities

$$D_g = \sum_{i=1}^{14} M[P_i, GIR_3]/2.10^{19} = 39\%.$$

We remind that the previous results were obtained using our matching method as presented in Table 4.2. In our method and all previous experimentation results, we have associated the SMAF autonomy scores 0 and -0.5 with the *A* scoring of AGGIR (see section 4.3). In a second simulation, we were interested in refining this association by a new association from SMAF to AGGIR: 0 to *A* and -0.5 to *B*. Our objective is to reflect the fact that the *A* evaluation in AGGIR concerns a perfect autonomy in performing a given activity of daily living. The *B* evaluation is associated to -0.5 because it describes the fact that the person is partially dependent. The results of our second simulation lead us to similar observations as discussed previously but with a significant incoherence in evaluating the dependency of persons. Indeed, we have observed that the degree of dependency in AGGIR was increased for people who are considered as relatively autonomous in SMAF. For instance, we observed a significant drop in the rates of GIR_6 and GIR_5 (i.e. AGGIR autonomous persons) and high matching (90.11%) between autonomous persons in SMAF (P_1) and persons with more dependency (GIR_4). Table 4.6 shows the percentages of matching between SMAF profiles and AGGIR groups using the new consideration of matching (0 to *A* and -0.5 to *B*).

Table 4.6 – Distribution percentages between SMAF and AGGIR using the new "-0.5 to *B*" association

	$\mathbf{GIR_1}$	$\mathbf{GIR_2}$	$\mathbf{GIR_3}$	$\mathbf{GIR_4}$	$\mathbf{GIR_5}$	$\mathbf{GIR_6}$
$\mathbf{P_1}$	0	0.826	3.060	90.111	5.564	0.439
$\mathbf{P_2}$	0	3.798	11.747	82.698	1.684	0.072
$\mathbf{P_3}$	8.10^{-15}	7.104	19.391	72.720	0.762	0.022
$\mathbf{P_4}$	6.10^{-9}	12.472	28.965	58.258	0.300	0.005
$\mathbf{P_5}$	6.10^{-7}	17.989	36.180	45.700	0.130	0.002
$\mathbf{P_6}$	9.10^{-5}	27.847	43.315	28.799	0.038	3.10^{-4}
$\mathbf{P_7}$	9.10^{-4}	37.266	45.702	17.021	0.010	3.10^{-5}
$\mathbf{P_8}$	0.008	46.381	43.920	9.688	0.003	5.10^{-6}
$\mathbf{P_9}$	0.058	58.477	37.786	3.679	4.10^{-4}	2.10^{-7}
$\mathbf{P_{10}}$	0.266	68.626	29.896	1.212	5.10^{-5}	5.10^{-9}
$\mathbf{P_{11}}$	0.693	75.454	23.457	0.395	3.10^{-6}	6.10^{-12}
$\mathbf{P_{12}}$	1.137	78.119	20.507	0.236	2.10^{-6}	2.10^{-11}
$\mathbf{P_{13}}$	4.171	84.135	11.675	0.019	1.10^{-8}	0
$\mathbf{P_{14}}$	19.671	77.257	3.072	6.10^{-6}	0	0

4.6 Discussion

The main goal of this contribution part targets a better understanding of the context of persons in order to provide monitored persons in e-health systems with services that meet their context and real needs. In order to reach this objective, we need to consider the most important person's activities which affect the performance of individuals in positive or negative situations. Therefore, an ideal platform that provides such e-health services should consider the most relevant activities to be monitored and evaluated. Our contribution has considered current models, used in the health domain, to evaluate the execution of the human activities. This step helped to gain a better knowledge of the medical evaluation tools and highlight their drawbacks that can be avoided in order to design a new e-health ecosystem which reflects well the real world and is easily adaptable to health institutions. To the best of our knowledge, our contribution is the largest and most complete study that considers the two most used models in the evaluation of activities of daily living. The attempt in [289] has performed a similar comparison between the geriatrics models but unfortunatlly with only a limited set of subjects. This limited set had not permitted to gain a complete vision about the limitations and incoherence of existing models.

Our complete simulation (20 trillion of possible evaluations) led us to observe that in general, an uneven distribution has appeared from the two dependency models with some incoherence in the evaluation of subjects' level of dependency. Our results have highlighted that the AGGIR model is not as comprehensive as SMAF, this is clearly shown in the following points:

- The mismatch between the levels of autonomy and dependency from AGGIR to SMAF.
- The distribution from the autonomy evaluation in AGGIR to the dependency in SMAF, on the contrary, the distribution from the dependency in AGGIR to the autonomy in SMAF.
- Finally, the AGGIR model is not covering all the important abilities that denote the real performance of individuals in achieving their daily tasks.

On the other hand, although the SMAF model covers multiple activities, it has shown weaknesses in some aspects. Indeed, the SMAF model lacks *validity* periods regarding the activities' evaluations and show some exaggerations by considering some activities in situations of severe dependency.

In the e-health ecosystem, linking validity periods to the evaluation of each monitored activity is of high importance if the system targets providing context-aware services. Indeed, in order to ensure efficient services in time, the validity of the evaluation should be dependent on the type of activity and the necessity of updates with a well-determined threshold. In order to optimize the e-health systems, some activities have not to be monitored or measure all the time. For instance, in severe dependency levels, it is not necessary to monitor the grooming activity all the time by models and platforms. This improves the architecture to sense only some activities which directly affect the lives of the monitored persons. Consequently, the system has to monitor only appropriate activities that could trigger some services.

Finally, in the context of e-health services, our simulations led us to realize that the existing models are inadequate and not efficient to give an accurate assessment about the human dependency. Indeed, the existing models do not reflect the real context of the person. As we have shown previously, the same subject can be considered as autonomous by using one model and seen as a dependent person in another model.

4.7 Conclusion

In this Chapter, the context of monitored persons has been considered by studying and comparing the existing health models used in the evaluation of dependent people. The focus was on accurately meeting the needs of dependent people for appropriate healthcare services. Our contribution has clearly shown that neither the SMAF nor the AGGIR models could fulfill the requirements of efficiency and reliability of e-health platforms services. Therefore, in order to further reduce the error rate in the existing evaluation models and to build efficient e-health ecosystems, we should improve the performance of the evaluation models. According to our experimentations and the proposed matching algorithm, the SMAF model provides a better knowledge than the AGGIR model regarding the evaluation of individuals needs of help and assistance. Covering the most important daily activities is important, however, the SMAF-like models need improvements in order to be adopted in future e-health platforms which accommodate both efficiency and reliability. Such improvements concern for instance: the linking of evaluations to validity periods, the selection of a sub set of activities that depend widely on the current situation (context) of persons, the determination of the required frequency to evaluate (sense) the activities, etc. In the next Chapters, we will enrich the SMAF model and make it ready to be included in our targeted context-aware e-health architecture that provides e-health services in a smart space. We will consider the compatibility with heterogeneous data sources and sensors on one hand, and with heterogeneous person profiles on the other hand.

CHAPTER 5

Context-Aware Adaptive Framework

Contents

5.1 Introduction

In e-health, context-aware systems refer to systems that can automatically acquire the person's information (e.g. health state and behavioral patterns) and are able to provide and adapt their services accordingly. Context-aware assisted living systems must have a global and full visibility of the person's context. This visibility includes a good understanding of the person's lifestyle in performing the daily activities and detecting anomalies in the behavior (Chapter4). Moreover, the context of persons should be achieved by extracting high-level of data integration and inference to build a new knowledge using several approaches and techniques.

The key challenge in such intelligent environments is to determine: *what*, *when* and *how* to monitor, gather and analyze data related to the person's context. Sensing and analyzing the daily activities should be tied to the *type* of the monitored activity, its *complexity*, *repeatability*, and the *duration* required to achieve it. The contribution of this Chapter aims to improve the effectiveness of e-health monitoring systems and keep a strong link with the existing medical knowledge and methods such as the models used in the geriatric domain, as discussed in the previous Chapter. The usage of such knowledge will help to design a new health monitoring framework and to improve the context-awareness of e-health services

In this Chapter, we target the development of an adaptive and context-aware framework for e-health monitoring system. The framework aims to facilitate the integration of e-health services in smart homes and health institutions. The framework learns the person's behavior, evaluates his dependency level, prevents major complications, and provide timely and context-aware services. The objective of the monitoring framework is to consider different activities with an optimized use of resources (e.g. network, energy, and processing) without compromising the quality of the monitoring and with a system's ability to detect abnormal situations. The targeted monitoring should dynamically be adapted to the context and situation of the monitored person and his history, the nature of monitored activities and existing relationships between activities.

The layout of this Chapter is organized as follows: the problem statement and motivation are presented in Section 5.2. The proposed framework and methodology are described in Section 5.3. The used approaches which provide a deep knowledge of the person's context by considering the person's profile, the activities, and the relationships between activities are explained in Section 5.4. In Section 5.5, a new adaptive algorithm for monitoring the activities of daily living is presented. A new strategy for generating long-term realistic scenarios is discussed in Section 5.6. Section 5.7 evaluate the adaptability of our monitoring approach. Finally, the conclusion of this Chapter is drawn in Section 5.8.

5.2 Problem Statement

Traditional e-health monitoring approaches and context-aware assisted living systems tend to manage all the sensed data with unconditional processing (Figure 5.1). Most of these approaches adopt a continuous monitoring that maintains the transfer data channels available all the time. The adoption of such approaches causes several issues that negatively affect the consumption of resources and the relevance of the system's decisions. A long-term monitoring involves particularly the storage, the energy consumption of multiple sensors and sinks, the computational cost required to analyze data, and the network usage that results in data transmission failure. Moreover, handling an important amount of continuous data usually leads to ignor the priorities in processing the data and when the system should apply relevant and quick decisions. The same situation occurs with physical monitoring applications, which assume a uniform time interval data sensing and analysis. In order to enhance the reliability of health data transmission and the availability of high relevant contextual information, we need to define efficient data summarizing

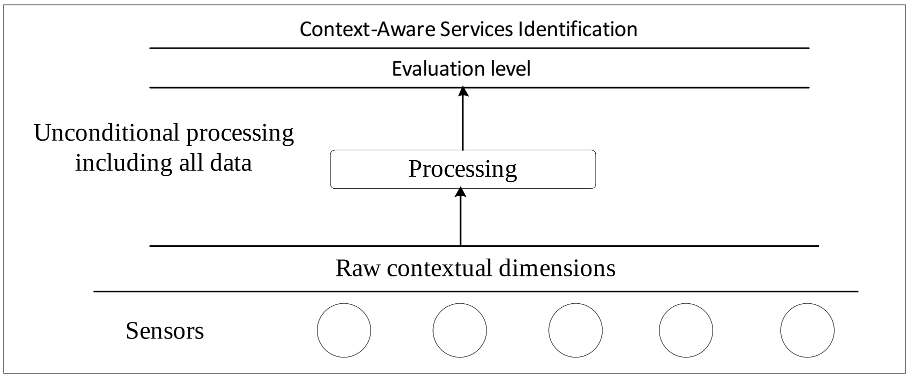

Figure 5.1 – Traditional e-health monitoring scheme with unconditional processing

algorithms and relevant data filtering mechanisms that consider all the variables of the person's activities and define a conditional monitoring scheme.

As presented previously in Chapter 4, in spite of the efforts made to develop e-health systems for monitoring and assessing the abilities of persons and their behavior, most of the existing systems operate in isolation from the requirements of the real-world and healthcare institutions. This fact contributes to a high incidence of projects that are either unsuccessful or not adopted [262]. Usually, there are several heterogeneous sensors and devices which are deployed in such e-health systems. This whole equipment increases both energy consumption and network traffic. Saving power can be ensured by using scheduling for sensor nodes or sentry-based algorithms in order to maintain the sensing coverage [290]. However, such schemes are not automatically adjusted at the execution time of monitoring. Therefore, we need a dynamic choice of monitoring modes. Some studies have resorted to specific types of wireless communication technology, such as Zigbee [152] or Bluetooth Low Energy (BLE) [67], to reduce the energy consumption. This remains restrictive since dealing with all available sensors and devices to gain a full visibility of the person's context is imperative. Single low-power consumption sensors were used in [291], while [140] used 167 sensors simultaneously. Therefore, there is a need to develop a new adaptive and efficient context-aware framework for e-health monitoring. We aim to provide dynamic updating and a reliable monitoring mode based on the person's context including the health status and behavior patterns.

5.3 The Framework of e-Health Monitoring

This section presents a new approach to characterize the adaptation of our the proposed monitoring system. We discuss our methodology in term of data processing then we discuss, in detail, the framework and the proposed adaptive monitoring approaches.

5.3.1 Data Processing Issues

In the context of the diagnosis of health situations, the variation of variables and parameters related to the health status does not always mean a change in the diagnosis. In the e-health monitoring and person evaluation, the major part of the data analysis and results of the evaluations concludes that there is no relevant change when compared to previous evaluations. Since the variability of the health conditions is usually much lower than the variability of the acquired signals themselves, the health professionals usually perform interpretation tasks sequences based on data priorities and limit therefore the diagnostic set to the most relevant results [292].

A health monitoring system which is performed either continuously or periodically using a uniform time interval with an unconditional processing scheme presents numerous issues. The continuous monitoring requires a huge amount of unnecessary data stream from heterogeneous sources and sensors. This data is usually sent to a coordinator (e.g. a gateway or a central node) and processed without any conditions (Figure 5.1).

Consequently, huge data with continuous analysis leads to insignificant impact regarding the person's situation and thus involves an excessive consumption of the system's resources. This situation is much more significant when we target a long-term monitoring based on the real-world evaluation models. Indeed, as explained previously, geriatrics models consider a rich set of activities such as meal preparation, eating, and walking. In an automatic system, the transmission, extraction, analysis, and recognition of data related to the person's activities require a lot of resources due to the involved continuous video and audio streams and complex recognition algorithms, machine learning mechanisms, etc. For instance, in the Ger'Home project of [293], the monitoring of elderly requires a complex transmission and processing of 24 GBytes of data only for 4 hours using 4 cameras. The senior monitoring project presented in [294] used the SAR dataset where the data size approximates 1.8 TBytes for only 10 days and with only 2 activities (*eating* and *walking*). A possible improvement of the existing approach is to define a new monitoring decision mechanism based on the importance, priority, and validity of the data. The validity of data denotes the time while the data sensing does not provide new values or while the new values are without any impact regarding the monitoring objectives.

Moreover, a periodic monitoring with fixed time intervals leads to two main unsatisfactory results. First, an inequitable monitoring in severe dependency and critical health status, which needs a high frequency of monitoring and data transmission. Second, a waste of effort and resources in case of stable situations. Our target system aims to determine what are the activities and contextual dimensions (variables) that need to be monitored in an optimized way either for the continuous or periodic monitoring.

5.3.2 Methodology

In order to reach our objective, we propose a non-uniform interval that we call a *validity period*. We define the validity period as the amount of time associated with each activity evaluation and determined by the condition of the person's profile (i.e. dependency level) and historical record. This leads to define different validity periods for each activity and within the same activity depending on the health status and person's record (e.g. normal behavior, chronic diseases, etc.). The validity period is influenced by the detection of the abnormal behavior of the monitored person in an

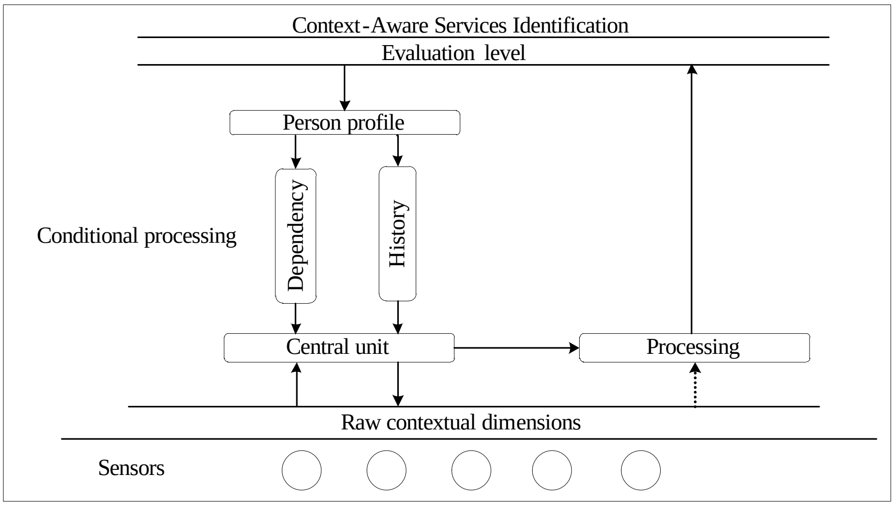

Figure 5.2 – Request-driven monitoring scheme

independent living. Such changes in patterns allow the system to notify caregivers in order to provide appropriate assistance and service. Periods are estimated on the basis of the patient's profile that considers the dependency level and the person's history in order to update the validity of data and the frequency of data requests.

To satisfy the previous requirements and in order to achieve a robust hybrid approach that is able to solve the issues discussed previously, we propose an adaptive context-aware monitoring framework with a conditional processing scheme. The adaptive framework offers several services such as the collection of high relevant and contextual data and the evaluation of the health status (mainly dependency level) of the monitored persons. The proposed approach allows to learn the human's lifestyle regarding the achievement of the activities of daily living and to detect the behavioral changes that may represent a risk for the monitored person. The framework adopts efficient monitoring frequencies for each activity and a dynamic update of sensing the activities. Consequentlly, the system will be able to detect any change and therefore, drive the used sensors into an optimal monitoring. Figure 5.2 presents our request-driven monitoring scheme. The person's profile, which includes the dependency level and historical record, represents a key factor in adapting the monitoring periods and to motivate the sensor nodes for an optimal sensing frequency and processing of the highly relevant data. The proposed approach solves the main issues associated with traditional monitoring schemes and improves the dependency evaluation models used in the geriatrics domain. Furthermore, the approach ensures an efficient collection and analysis of data for the prediction of the person's behavior.

5.3.3 Framework Description

In our context-aware approach, the human daily activities represent the *context*. It is used as the base layer for the different functionalities such as sensing, processing, and recommending required services. We illustrate the framework of our adaptive and context-aware system in Figure 5.3. The general scenario concerns a person who evolves in a smart space where adequate sensors are properly placed.

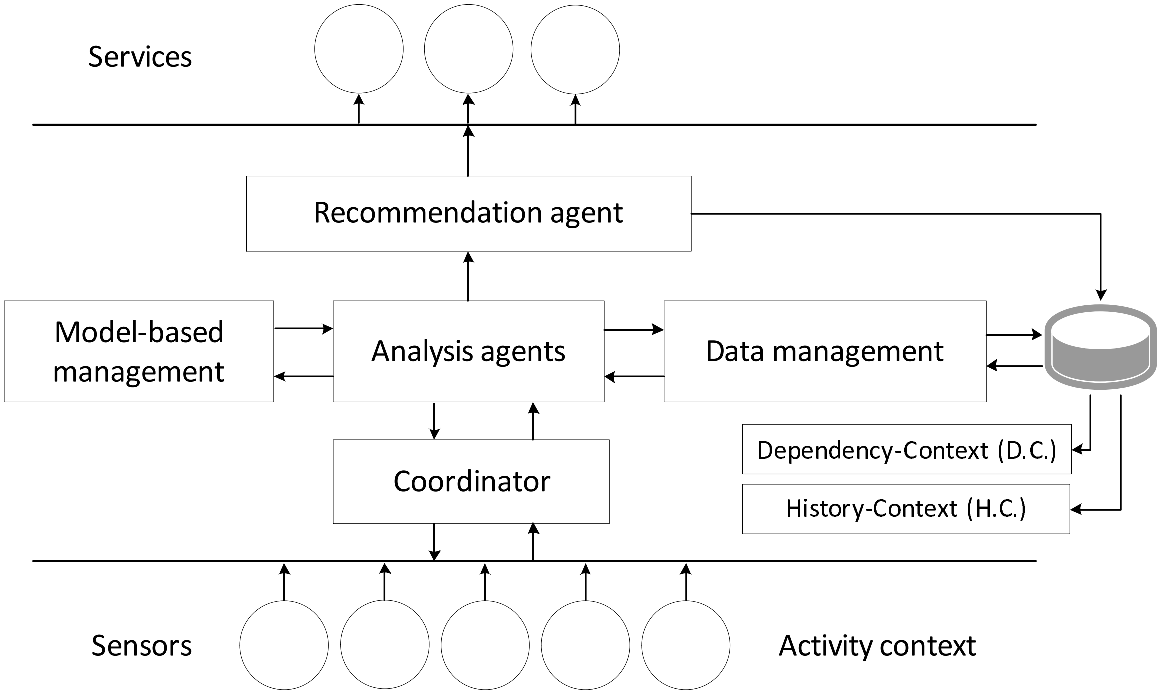

Figure 5.3 – Components of the framework for the e-health monitoring

Data is collected and transmitted by sensors in a continuous or periodic way. The coordinator ensures the analysis and the processing of the received data. Streams coming from several heterogeneous sources are handled by the *data management* system which is able to apply traditional database primitives such as adding, searching and updating data. Thanks to the data management system, the *analysis agents* considers the person's profile which includes the *dependency-context* (D.C.) and the *history-context* (H.C.) for a specific period of time. The first inference is applied to set up the monitoring mode. This is achieved thanks to the connection between the analysis agent and the model-based management. The latter selects the geriatrics model (e.g. SMAF) which is in turn considered in the data management and combined with input data to adjust the monitoring. Finally, the data sensing and processing will result in recommending healthcare services adapted to the current needs of the person.

5.4 Approaches

In order to dynamically update the monitoring of the person's activities, our adaptive context-aware monitoring system defines three approaches used together: the *Activity per Activity* approach, the *Global* approach, and *Relational* approach, (Sections 5.4.1, 5.4.2 and 5.4.3). These approaches are applied to adapt the e-health monitoring by learning the human behavior, evaluate the health conditions, and dynamically update the monitoring mode.

5.4.1 Activity per Activity Approach

The aim of this approach is to consider and evaluate each monitored activity separately. This approach takes into account the nature of each activity and the required time for the monitoring. This approach is particularly important during the initial monitoring stage and helps to learn the evolution of the person's behavior in performing the daily activities.

Thanks to our previous investigation (Chapter 4), we consider a rich set of activities linked to the scales used in geriatrics. This set includes the SMAF activities and extends them with additional ones. For example, eating, toileting, reading and watching TV. We associate dynamic metadata to each activity depending on its complexity and the necessary time to monitor it. Such metadata include the category of each activity, the monitoring frequency, duration of the monitoring, possible used sensors, and scores used to determine the optimal monitoring mode to be applied. Table 5.1 presents the considered activities with these linked information. The *frequency* is used to determine when the monitoring should start with a range of the sensing frequency (x values) while the *duration* specifies how long the monitoring must be performed. The classes of activities are defined to distinguish the level of consumption of the resources (e.g. network traffic, bandwidth, power, etc.). As in geriatric models, scores are used to quantify the ability of the person's to achieve the activities.

Table 5.1 – The *activity per activity* approach

	Activity	Frequency	Duration	Class	Possible sensors or devices	Scores
ADL	Eating	$x = 3$ (i.e. each 3 days)	Category II[2]	high	IP Camera, sound detector, light switch, door fridge sensor, motion sensor and/or RFID...	4 modalities[4] with a step of $P/(4x)$
	Dressing	$x = 10$	Category I[1]	high	door sensor aperture, IP Camera, sound detector, motion sensor and/or RFID...	4 modalities[4] with a step of $P/(4x)$
	Washing	$x = 10$	Category I[1]	medium	ultrasonic water flow meter, humidity, light, sound detector, temperature and/or motion sensor...	4 modalities[4] with a step of $P/(4x)$
	Grooming	$x = 10$	Category I[1]	medium	light, sound detector, hairdryer, motion sensor and/or RFID...	4 modalities[4] with a step of $P/(4x)$
	Urinary function	$x = 3$	Category II[2]	medium	ultrasonic water flow meter, light, sound detector, flushes switch ,motion sensor and/or RFID...	4 modalities[4] with a step of $P/(4x)$
	Bowel function	$x = 3$	Category II[2]	medium	ultrasonic water flow meter, light, sound detector, flushes switch, motion sensor and/or RFID...	4 modalities[4] with a step of $P/(4x)$
	Toileting	$x = 3$	Category II[2]	medium	light, sound detector, flushes switch, motion sensor and/or RFID...	4 modalities[4] with a step of $P/(4x)$
Mobility	Transfers	Computed	Category III[3]	low	single inertial sensor...	4 modalities[4] with a step of $P/4$
	Walking inside	Computed	Category III[3]	low	floor plan, indoor GPS, motion sensor and/or RFID..	4 modalities[4] with a step of $P/4$

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Table 5.1 – continued from previous page

	Activity	Frequency	Duration	Class	Possible sensors or devices	Scores
	Walking outside	Continuously		low	door sensor aperture, and motion sensor...	4 modalities[4]
	Not considered activities: Donning prosthesis, Propelling a wheelchair, Negotiating stairs					
Communication	Vision	Computed $x = 30$	Category III[3]	low	TV questionaries' achieved by the person [8]...	4 modalities[4]
	Hearing	Computed $x = 30$	Category III[3]	low	TV questionaries' achieved by the person...	4 modalities[4]
	Speaking	Computed $x = 30$	Category III[3]	low	TV questionaries' achieved by the person...	4 modalities[4]
Mental functions	Behavior	$x = 30$	Category III[3]	low	TV questionaries' achieved by the person...	4 modalities[4]
	Judgment	$x = 30$	Category III[3]	low	TV questionaries' achieved by the person...	4 modalities[4]
	Orientation	Computed	Category III[3]	low	floor plan, indoor GPS, motion sensor and/or RFID..	4 modalities[4] *Step* $= P/4$
	Memory	Computed $x = 30$	Category III[3]	low	TV questionaries' achieved by the person...	4 modalities[4]
	Comprehension	$x = 30$	Category III[3]	low	TV questionaries' achieved by the person...	4 modalities[4]
IADL	Housekeeping	$x = 10$	Category I[1]	medium	power sensor, sound detector and/or motion sensor..	4 modalities[4] with a step of $P/(4x)$
	Laundry	$x = 10$	Category I[1]	medium	power sensor, sound detector and/or door sensor aperture..	4 modalities[4] with a step of $P/(4x)$
	Meal preparation	$x = 3$	Category II[2]	high	washing dishes, mixer tap, gas, oven, toaster, light switch, door sensors and IP camera, sound & motion detector, RFID..	4 modalities[4] with a step of $P/(4x)$
	Telephone	$x = 10$	Category I[1]		answer telephone	4 modalities[4] with a step of $P/(4x)$
	Medication use	$x = 3$	Category I[1]	low	door sensor aperture, and motion sensor..	4 modalities[4] with a step of $P/(4x)$
	Not considered activities: Transportation, Shopping, Budgeting					
Other	Watching TV	$x = 10$	Category I[1]	high	Power sensor, Pressure sensor, IP Camera, and/or sound detector..	4 modalities[4] with a step of $P/(4x)$
	Sleeping	$x = 3$	Category II[2]	low	pressure sensor and motion sensor..	4 modalities[4] with a step of $P/(4x)$
	Reading	$x = 10$	Category I[1]	high	IP Camera, and/or sound detector..	4 modalities[4] with a step of $P/(4x)$
	Weight	$x = 30$	Category I[1]	low	weight sensor ..	

[1] sensor is active till the activity occurs, then the next monitoring will be after the x period, [2] when the activity occurs, the monitoring will be during the next 24h, [3] the evaluation is based on the relationships between activities, [4] possible scores are : 0, -1, -2 and -3

In order to start the monitoring mode, we first set the monitoring values for each activity regarding the initial frequency (i.e. the x value) and the duration. The activities are classified into three main categories of monitoring. For instance, *Category II* includes the activities that need to be monitored over the 24 hours such as *Toileting*. As we can see in Table 5.1, x is fixed to 3 for the *Toileting* activity. This means that the system will trigger a new monitoring each 3 days. Each new monitoring takes 24 hours since the activity belongs to *Category II* (Table 5.1). *Category I* includes activities like *Washing*, *Grooming*, and *Dressing*. When the selected frequency (the x value) is 10 and since duration is *always active* till the activity occurs, so the next round of monitoring will be triggered after the 10 days.

In our previous example of *Category II*, in order to evaluate activities such as *Toileting*, *Eating*, and *Sleeping*, the system monitors the given activity, as mentioned, each 3 days during 24 hours. This leads, during a period of P=30 days, to a total of 10 results. Among these 10 results, each single result indicates if the person succeeds or fails to perform the activity. The results are used to incrementally judge the person's ability through the duration of the monitoring mode. To evaluate the activities of *Category I*, such as *Washing*, *House keeping* and *Dressing*, it is only required to check if the activity is achieved or not in order to be taken into consideration (i.e., counted as number of achievements). For *Category III*, we use the existing logic relationships between activities. For instance, the *Memory* variable is associated with the ability of the person to remember to *Take medication*. The monitoring checks the person's behavior as follows. If the current number of performed activities is less or greater than the last observed average (mainly regarding the repeatability and duration), an abnormal behavior is detected. When an anomalous behavior is detected, the monitoring is extended for an extra amount of time. Otherwise, the system considers single results that quantify the person's behavior when the number of achieved activities is more than or equals values defined in geriatrics. For ease of understanding, let us consider the following example regarding the *Toileting* activity. If the system did not detect an abnormal behavior and if the observed number of *Toileting* is greater than or equals to 2, a single result (i.e. the value of 2) will be kept for a given time, such as for one day.

Based on the real-world geriatric models, the ability to perform a given activity (i.e., the degree of dependency) of the monitored person is evaluated using scores. Our adaptive system regularly evaluates the degree of dependency each period of time (called P). During the P period and for each activity, the system counts the number of occurrences where the person correctly achieves the activity. The associated counter, used in our algorithm, is called *activityResults*. The counter is updated depending on the frequency of sensing. Specifically, it is updated each x time. This means, after each x time, the system senses the person's environment to checks if the person succeeds to perform the activity. If it is the case, the system increments the *activityResults* counter. The value of the counter is reset at the end of each P period. The following example illustrates this method. Consider an activity A required to be achieved by the monitored person once a day in a normal behavior. If P = 30 days, x = 3 days, and *activityResults* = 9, then this denotes the following scenario. The system calculates the dependency level regarding the activity A each 30 days; thanks to sensors, it counts the times where A was correctly achieved each 3 days. The example shows that the activity A was achieved correctly by the monitored person 9 times (i.e. *activityResults* = 9) during the last 30 days.

Scores resulting from the evaluation of dependency can be one of the following values: 0, labeled *Autonomous* or *A*; -1, labeled *Supervision (S)*; -2, labeled *Need help (H)*; and -3, labeled *Dependency (D)*. In order to connect the value of the activity counter (*activityResults*), explained previously, to these four modalities (i.e. A, S, H or D), we define four linear intervals. Intervals are defined with a step of $\frac{P}{4.x}$ and associated to the four modalities as follows:

$D \equiv [0, \frac{P}{4.x}[$;
$H \equiv [\frac{P}{4.x}, 2.\frac{P}{4.x}[$;
$S \equiv [2.\frac{P}{4.x}, 3.\frac{P}{4.x}[$; and
$A \equiv [3.\frac{P}{4.x}, \frac{P}{x}]$.

For instance, if we consider the previous example (i.e. with $P = 30$ days, $x = 3$ days and $activityResults = 9$), then the following intervals are considered:
$D \equiv [0, 2.5[$;
$H \equiv [2.5, 5[$;
$S \equiv [5, 7.5[$; and
$A \equiv [7.5, 10]$.

As we can observe, the value of *activityResults* (i.e. 9 in our example) belongs to the last interval A. Consequently, based on the observed activity score (*activityScore*), the system evaluates the monitored person as *Autonomous* in achieving the activity A for the last 30 days.

5.4.2 Global Approach

The main objective of this approach is to determine the optimal degree of data sensing (i.e. frequency) and in order to avoid the sensing and processing of unnecessary and irrelevant data which is unfortunatlly an issue of the traditional monitoring systems. Moreover, we aim to avoid the exaggerations of the existing dependency evaluation models that requires the computation of all the activities at all the levels of dependency even in severe ones, as it presented in our previous investigation (Chapter 4).

Request-driven monitoring approaches [292] represent a good candidate to optimize the continuous monitoring. Therefore, our adaptive monitoring considers the global dependency evaluation of the person as the basis for increasing or decreasing the monitoring frequency. This approach is based on the initial x value, discussed previously, and applies a global evaluation of the person abilities based on geriatrics evaluations.

The idea is to define a dynamic monitoring frequency that dynamically adapts the initial x value depending on the person's ability (from autonomy to severe dependency) and relying on the nature of the category of monitored activities such as ADL and IADL. To reach this objective, and based on our work in Chapter 4, the SMAF model is endorsed as the basis for the real-world evaluations [5]. As presented previously, SMAF defines 14 dependency levels (called *profiles*) from *profile 1*, which refers to autonomous persons, to *profile 14*, which refers to completely dependent persons. These levels are based on the evaluation of the activities using the five defined functional abilities: activities of daily living (ADL), mobility, communication, mental functions, and instrumental activities of daily living (IADL).

Table 5.2 shows our system's dynamic updates of the x value regarding the current person's profile which is periodically evaluated. As we can see, the value of x depends to the class of the activity (i.e. ADL, mobility, communication, mental functions, and IADL) and the modalities of the dependency as defined in the SMAF model (i.e. autonomous, difficulties, etc.). For instance, for autonomous persons with profiles P_1 and P_2, the system uses the default x value (initialized in the

Table 5.2 – The *Global* approach of monitoring

		ADL	**Mob.**	**Com.**	**M.F.**	**IADL**
C_1	P_1	$x = inf.$	$x = inf.$	$x = inf.$	$x = inf.$	$x = x/1$ (initial x)
	P_2	$x = inf.$	$x = inf.$	$x = inf.$	$x = inf.$	$x = x/1$
	P_3	$x = inf.$	$x = inf.$	$x = x/1$	$x = x/1$	$x = x/2$
C_2	P_4	$x = inf.$	$x = x/1$	$x = x/1$	$x = inf.$	$x = x/2$
C_3	P_5	$x = x/1$	$x = inf.$	$x = x/1$	$x = x/1$	$x = x/3$
C_2	P_6	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/3$
C_3	P_7	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/2$	$x = x/(3-1)$
	P_8	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/2$	$x = x/(3-1)$
C_2	P_9	$x = x/2$	$x = x/2$	$x = x/1$	$x = x/1$	$x = x/(3-2)$
C_3	P_{10}	$x = x/2$	$x = x/1$	$x = x/1$	$x = x/2$	$x = x/(3-2)$
C_4	P_{11}	$x = x/2$	$x = x/2$	$x = x/1$	$x = x/2$	$x = inf.$
	P_{12}	$x = x/3$	$x = x/2$	$x = x/1$	$x = x/2$	$x = inf.$
	P_{13}	$x = x/3$	$x = x/3$	$x = x/1$	$x = x/2$	$x = inf.$
	P_{14}	$x = x/3$	$x = x/3$	$x = x/2$	$x = x/3$	$x = inf.$

Autonomy, Difficulties, Supervision, Help, Dependence [5]

previous approach) for the IADL activities and ignores the other classes of activities(using a setting of x to an $infinity$ value). Notice that for dependent persons, starting from P_6, all the activities (belonging to all the classes) are monitored with the default value of x and with a high frequency of monitoring when the activities belong to the IADL class. This is motivated by the fact that persons belonging to profile P_6 are suffering from a high dependency in achieving their IADL activities such as meal preparation and medication use.

Our general rule, within the same category of activities, is when the dependency increases, the x value decreases except for the IADL activities in profiles P_7 to P_{14} as we can see in Table 5.2. Indeed, since IADL activities are lost first (i.e. before the loss of abilities regarding the other classes of activities), this means that a person who is not able to achieve the IADL activities will start, in the future, to need help in achieving the other kind of activities. This situation starts from P_7 (Table 5.2). Consequently, we start decreasing the x value for IADL from the profile P_7. For, and only for, the IADL activities, the x value starts to become $infinity$ (i.e. no monitoring is needed anymore) when the person starts to need help in achieving the majority of his activities (from P_{11} to P_{14}). In this situation, the person enters to the called *long-term care facilities* (LTCF).

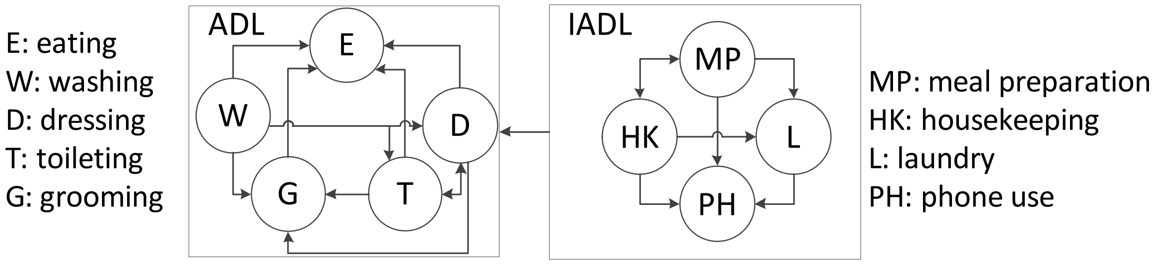

Figure 5.4 – Relations between activities

5.4.3 Relational Approach

This approach takes advantage of the two approaches discussed previously. It focuses on the logical relationships that can exist between the monitored human activities. Based on the existing logic related to the person's ability in performing different activities, we can improve the monitoring mode and optimize the system resources without compromising the level and quality of the monitoring service and with maintaining the system's ability to detect abnormal situations. The digraph $\mathcal{G} = (V, A)$, presented in Figure 5.4, identifies a subset of the identified relationships between functional abilities ($a_i \in V$) within and between the ADL and IADL categories.

An arc $e = (a_i, a_j)$ means that if the person is able to achieve correctly the a_i activity so he is able to achieve correctly the a_j activity. Consequently, if the system detects a good ability in achieving the activity a_i correctly, no monitoring will be needed regarding the a_j activity. Hence, the x value of a_j is set to $infinity$ till the next detection of any change regarding the person's abilities and behavior.

5.5 Proposed Algorithm

In Figures 5.2 and 5.3, we summarized our proposed methodology and context-aware algorithm for monitoring the activities of daily living of individuals such as elderly and dependent persons. The idea is to apply the different approaches, discussed previously, in order to provide an efficient monitoring mode that is dynamically adapted to the current situation (context) of the person. The new proposed algorithm simulates data series with a time evolution variable (i) and applies the previous approaches on different input scenarios generated for one year (Algorithm 4, line 2) and coming from our *eHealth Monitoring Open Data Project* [295]. We consider 29 activities (Table 5.1) with 9 sub-activities such as *washing hand/face*, *hair dry*, and *makeup* for the *grooming* activity ; *wash dish*, make coffee, *make tea*, *make sandwich* (toaster), *make hot food* (microwave), and *move dish* for the *meal preparation* activity.

All the considered activities are associated with a monitoring time ($MTime$) which depends on the value of x (i.e. the sensing frequency). The x value, related to the frequency of the monitoring, depends on the nature of the monitored activity and is updated regarding the evolution of the context (profile) of the person, such as the loss of abilities in achieving some tasks. These abilities are computed using scores associated to the different activities (see Algorithm 4, lines 9, 16 and 23). The activity score is computed in the $SMAFScore$ function (line 30 Algorithm 4). This score (presented in Algorithm 5 and described in Section 5.4.1) is tested using the four defined modalities A, S, H, and D. The person's profile is then computed using the *computeSMAFProfile* function (Algorithm 4, line 32). The person's profile determines the new x value and monitoring time (*MTime*) for each activity using the *GlobalApproachUpdates* procedure (see line 33 in Algorithm 4 and see Algorithm 5). Our second and third approaches are applied using the *GlobalApproachUpdates* and *RelationalApproachUpdates* functions (lines 33 and 34 in Algorithm 4) which are presented in Algorithm 5. Our algorithm uses adaptive monitoring periods with the required duration and includes the determination of the next monitoring time and the frequency in which the used sensors should send their data. The algorithm allows the evaluation of the network traffic and energy consumption implied by the adaptive monitoring (lines 10 and 17 in Algorithm 4).

5.6 Generation of Daily Activities Scenarios

In order to evaluate the efficiency of our proposed adaptive system, we need to experiment it with a serie of rich and realistic scenarios that describe the activities of daily living performed by a single person and with different levels of dependency. The generation of simulated ADL-based scenarios (datasets) can provide sufficient data to help the design and validation of approaches defined for e-health smart homes and assisted living systems [296].

One identified key requirement for such simulation is that the daily life scenarios should consider events and human activities in a realistic way. This implies to be as close as possible to the real life of persons like elderly and dependent persons. Moreover, scenarios for a long time period allow the evaluation of various aspects of our proposal such as the dynamic monitoring and the recongnition of the health decline impact. Real-life platforms require complex implementations including an important number of required sensors used to consider a rich list of activities including those defined in geriatrics. Hence, in order to make a proposed system ready for the operational environment, a real-life implementation requires a long-time testing where the this testing involves the life of humans. Real-life platforms are faced with a lack of flexibility regarding the aim to vary the set of used sensors and may represent a risk for the person's life if algorithms should evolve during the testing. Another identified requirement for the desired input scenarios is to consider abnormal situations that may occur during the monitoring of the person. In sum, in order to fulfill the previously identified requirements and gain an efficient evaluation tool, it is necessary to select realistic, rich and flexible scenarios that take into consideration various human activities monitored during a long period.

It is worth mentioning that the use of simulated data in health informatics research is common practice [297]. It emerged as an alternative approach and plays a significant role to develop and validate health monitoring systems [296] [298] [299]. Simulation methods can handle different activity trends, avoid tedious lab experiments or real-world deployments, test safely uncommon scenarios of everyday life (instead of waiting for unpredictable real-life apparitions), managing sensor distribu-

Algorithm 4 Adaptive Monitoring

```
procedure AdaptiveMonitoring
    A ← 29 activities; N ← 365 * 24 * 3600 seconds;
    activity ← readLine(inputScenario); nxtMTime(a_i) ← 0;
            ▷ read the first activity & initialize "next monitoring time" for activities
    for i = 1 → N do
            ▷ simulate the time evolution, i is the current instant
        if i == startingTime(activity) then
            switch activity do
                    ▷ see Section 5.4 & Table 5.1 for Categories
                case Category I :
                    if i ≥ nxtMTime(activity) then
                        activityResults(activity)++;
                        compute network traffic and power consumption;
                        updates nxtMTime(activity);
                    end if
                case Category II :
                    if i ≥ nxtMTime(activity) and
                     i ≤ nxtMTime(activity) + 24h then
                        temporaryActivityResults(activity)++;
                            ▷ after 24h activityResults will be computed
                        compute network traffic and power consumption;
                    end if
            activity ← readLine (inputScenario);
        end if
        for each a in Category II do
            if i ≥ nxtMTime(a) + 24h then
                computeActivityResults (a);
                    ▷ after 24h activityResults is computed
                    ▷ using temporaryActivityResults(a)
                updates nxtMTime(a);
            end if
        end for
        if mod (i, 30 days) == 0 then
                ▷ each month, the activityScore is computed (see Section 5.4)
            for l = 1 → A do
                activityScore(a_l) ←
                SMAFScore(activityResults(a_l));
            end for
            profile ← computeSMAFProfile(activityScores);
                ▷ for computing the SMAF score, see Chapter 4
            GlobalApproachUpdates(profile);
            RelationalApproachUpdates(activityScores);
        end if
    end for
end procedure
```

tions, assessing algorithms used in the area of activities or in the behavioral sciences [299].

In this context, many efforts have been made to design and apply simulators which imitate activities of daily living. For instance, authors in [116] simulated the behavior of a patient living in a smart home. The simulated data have been proposed as a mean to facilitate the development and validation of activity monitoring systems

Algorithm 5 Helper Functions and Procedures

function SMAFScore($activityResults(a_l)$)
  $P \leftarrow 30\ days$; $step \leftarrow P/4\mathcal{X}\_Value(a_l)$; ▷ *see Section 5.4.1*
  $v \leftarrow activityResults(a_l)$;
  switch v **do**
    case $v \geq 0$ and $v < step$ **: return** -3;
    case $v \geq step$ and $v < 2.step$ **: return** -2;
    . . .
end function

procedure GlobalApproachUpdates($profile$)
  switch $profile$ **do**
    case P_1 **:**
      updates $nxtMTime(a_i)$; updates $\mathcal{X}\_Value(a_i)$; ▷ *this is applied for all the activities a_i (Table 5.2)*
    case P_2 **:** . . .
end procedure

procedure RelationalApproachUpdates($activityScores$)
  if $activityScores(a_i) == 0$ **then** updates $nxtMTime(a_j)$; ▷ *If a_i is achieved autonomously, do not* ▷ *monitor related activities a_j, see Section 5.4.3*
  end if
end procedure

for older adults at home [296]. Furthermore, several approaches and algorithms for monitoring the behavior of elderly in smart environments were tested by using simulated data such as in [105, 153, 300, 301]. Authors in Medjahed et al. [153] described a fuzzy logic system for recognizing activities in a home environment using a set of sensors such as physiological sensors, detection sensor, microphones, and infrared sensors. Their proposed method was experimentally achieved on a simulated dataset in order to demonstrate its effectiveness. Authors in Sim et al. [301] used correlated patterns in activity recognition systems for assisting dementia patient in performing the ADL activities. Their experimental results, based on simulation data, show that using correlated patterns is more accurate than frequent patterns in high dimensionality and a large volume of data. More recently, a context-aware model for monitoring ADL in ambient assisted living was presented in Forkan et al. [105]. The authors used machine learning and statistical methods for behavioral change detection and abnormality prediction. Their experimentations were applied on a dataset that was generated synthetically. In this contribution, our proposed system is tested against simulated data that were generated based on statistical methods.

Simulating realistic daily activities is a challenging task since the achievement of activities is usually subject to a number of factors such as basic needs, lifestyle, physical and mental abilities [296]. In addition, simulated scenarios should be impacted by the person's level of dependency and consider different person profiles. Unfortunately, real-life monitoring within a reasonable time, example during one year, can not provide a good testing environment (Table 5.3). Indeed, such monitoring

Table 5.3 – Comparison between real-world datasets and our monitoring dataset

Dataset	Activities[1]	Duration	Geriatric models	Sensor heterog-eneity	Time slices for activities	Profile changes
Kasteren (A, B and C)[2]	ADL (3 activities)	22 days (A) 12 days (B) 17 days (C)	no	low class	33,120 (A) 17,280 (B) 24,480 (C)	no
Ordonez (A and B)[3]	ADL (3 activities)	14 days (A) 21 days (B)	no	low class	20,160 (A) 30,240 (B)	no
MIT[4]	ADL (4 activities) IADL (2 activities)	15 days	no	low, medium, and high classes	690 (for annotated activities)	no
CASAS Kyoto/Daily life 2010[5]	ADL (4 activities) IADL (2 activities)	8 months	no	low class	3,741	no
Our dataset	ADL (5 activities + actions), IADL (5 activities + actions	5 years	yes (SMAF)	low, medium, and high classes	13,933 (1 year) 14,240 (1 year) 10,981 (1 year) 7,0238 (1 year) 11,436 (1 year)	yes (4 changes)

[1] Activities as defined in [5], [2] Kasteren in [302], [3] Ordonez in [303], [4] MIT in [304], [5] CASAS in [305]

will not allow the evaluation of our proposal regarding our focus on adaptability and predictability. Moreover, abnormalities and changes related to the dependency level should occur during the monitoring in order to validate the ability of our system to detect them. It is obvious that abnormalities are risky for real subjects and significant changes of the dependency degree, as observed in geriatrics, can take a very long time to appear. To the best of our knowledge, existing real-world datasets monitor persons belonging to the same profile with the same dependency level, see Table 5.3. For the evaluation of resource consumption, only a limited set of sensors, or class of sensors, was used in the explored datasets. This is why we require considering heterogeneous classes of sensors in terms of energy consumption and network use. All the investigated real-world datasets that monitor elderly did not consider a rich set of activities (such as including ADL, IADL, and additional activities) for a long period. They involve a subset of activities (sometimes simple human actions) and are not linked to geriatric models used by health professionals. Hence, they fail in providing a good visibility regarding the person's context.

Several existing simulation studies were describing the daily behavior profiles which often provide limited information such as regarding the spatial context of the person (e.g. simulated room transitions). The authors in [116] and in [306] used Markov Models to estimate the location (room) of the person. They used different models in different periods of the days but each day uses the same model set. Consequently, the scenario of every day has similar possible results [307]. The simulation defined in [116] used a model were an activity at time $t + 1$ depended on the activity achieved at time t.

5.6.1 Strategy Description

We define a new scenario generation strategy based on the Markovian models. We aim to provide a long and rich realistic sequences of activities that can be achieved by persons, mainly the elderly, with different levels of disabilities and including autonomous persons. To achieve this objective, we were based on the variable-length Markov class (VMM [308]) which helps in increasing the expressivity level while generating the sequences of daily living activities. Such a sequence is denoted as follows:

$$s = a_1, a_2, ..., a_l$$

where l is an order greater than one. The set of a_i activities, represent the human actions performed for the different activities as defined in geriatrics. Thanks to the results of our previous Chapter, we were mainly focused on the SMAF model. For each action a_i, we associate a starting time (*startingTime*) and a pseudo-random variable for durations ranging from a defined lower to upper bounds:

$$activityDuration \in [aD_{min}, aD_{max}]$$

A pseudo-random transition time (*transitionTime*) is used from the end of each action a_i to the starting time of a next action a_j. The time of transitions varies from a predefined lower limit to an upper limit:

$$transitionTime(a_i, a_j) \in [tT_{min}, tT_{max}].$$

In order to simplify our generation process and to keep outputting realistic sequences, we define five transition matrices which correspond to the following day periods: from 8.00 am to 11.00 am, from 11.00 am to 2.00 pm, from 2.00 pm to 5.00 pm, from 5.00 pm to 10.00 pm, and from 10.00 pm to 8.00 am. In addition, to enrich the degree of context-awareness, we define two other matrices for particular periods and days such as for Saturday and Sunday since these days could include some specific activities. The most probable activities that can be achieved by the person during a given period are associated with highest probabilities. This is true, for instance, for the *Taking a shower* activity in the morning, the activity of *Having dinner* in the evening, possible *House keeping* activities on Saturday and the event of *Leaving the home* for a long period on Sunday.

We use the Markov property in our generation strategy of scenarios. In concrete terms, seven matrices $\mathcal{M}_{p \in \{1\ to\ 7\}}$ are defined and used to explore the different activities transitions within these matrices. Each state a_i is a possible human action or activity as defined in the real-world geriatrics models. Next actions, a_j, follow the probability:

$$P(a_j \mid a_i) = \mathcal{M}_p(a_i, a_j).$$

The definition of the P probabilities is performed according to each person's profile as defined in the SMAF model. When a new action a_j is selected, it is appended to the sequence s which is the sequence of the current activities performed by the person.

Even if the used probabilities are strongly related to the real-world and the geriatric SMAF model, relying exclusively on probabilities for the activities transitions provides as a result what is knows as a *random walk* approach. In order to improve the generation of sequences, it is important to avoid the possible drawbacks of the random walk approach. We cite, mainly, the drwabacks of possible consideration of less probable sequences and the lack of control during the construction of sequences.

Indeed, an *absolute* random walk could end up with a sequence that ignores a required activity in a given day period (e.g. morning or afternoon). This may occur even if the person has the ability to achieve the activity. Another example is the possible generation of a sequence that takes a long time that significantly exceeds a given day period. To tackle these issues, we control the previous generation process by adopting a set of constraints. This way leads to define a *pseudo* Markovian model where the s sequences rely on the probabilities of transitions but under certain conditions. Each transition, from a current state a_i to a possible next state a_j, is checked using the introduced constraints. If the transition to a new state violates, at least, one constraint, the controlled random walk is reoriented to another possible state.

Constraints and matrices $\mathcal{M}_p$ guarantee, by construction, the following properties: (a) a finite and convergent generation of sequences, and (b) transitions that are faithful to the person's dependency level as defined in SMAF profiles [5]. Two main constraints are used: the frequency of occurrence

$$f(a_i) \in [f_{min}, f_{max}]$$

of some particular activities and the duration *sd* of a sequence. This means that a given activity can occur at least f_{min} times (that could be null) and at most f_{max} times. This constraint controls how much particular activities should appear in a sequence. For instance, the number of *Grooming* and *Eating* activities for an autonomous person. When all the non-null frequencies defined in constraints are satisfied, the process stops if the duration of the whole generated sequence reaches or starts to exceed the *sd* value. The value of *sd* is computed as follows:

$$sd = \sum_{i=1}^{l} activityDuration(a_i) + \sum_{i=1}^{l-1} transitionTime(a_i, a_{i+1})$$

where the sequence s is composed of a_1, a_2, .., and a_l activities. Table 5.4 shows an overview of one used matrix ($M_{[14:00\check{}17:00]}$) in terms of selected list of activities with the used bounds (i.e. minimum and maximum values) of activities durations and number of occurrences.

The following matrix $M_{[14:00\check{}17:00]}$ presents the probabilities of transitions and the bounds (in seconds) used to generate a random transition time within the given interval. All the defined matrices, used graphs, and generated scenarios can be accessed online using our *eHealth Monitoring Open Data Project* [295].

Table 5.4 – An overview of the matrix $M_{[14:00\check{}17:00]}$ used in scenarios generation

Id.	**Activities**	**Duration bounds** D_{min} and D_{max} **in seconds**	**Frequency bounds** f_{min} and f_{min}
1	Sleep	[7200, 9000]	[1, 1]
2	Washing H/F	[180, 360]	[0, 4]
3	Toileting	[300, 600]	[0, 2]
4	Make coffee	[300, 600]	[0, 1]
5	Cell use	[600, 1800]	[0, 3]

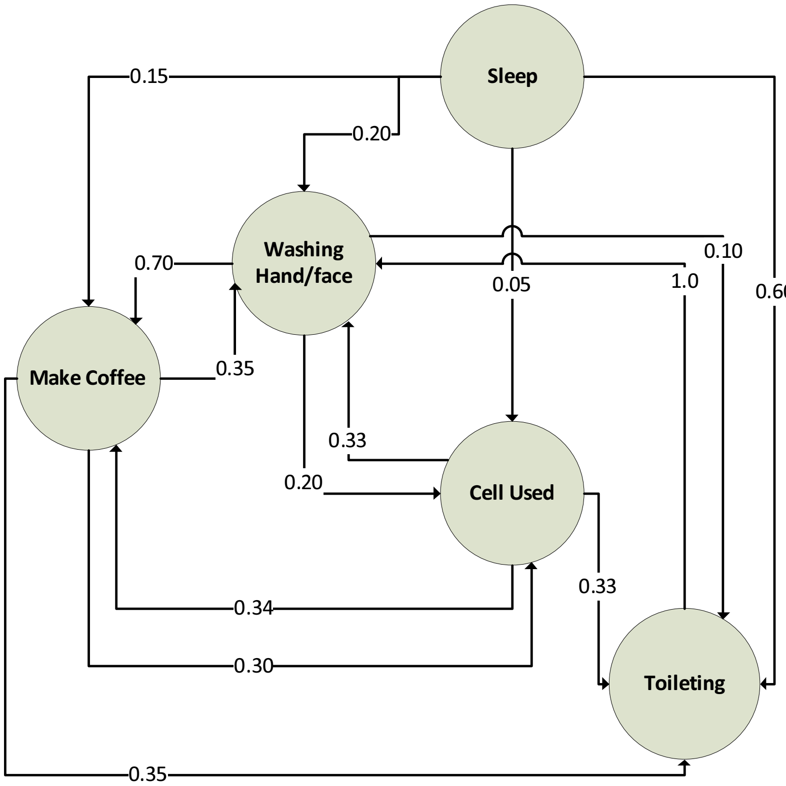

Figure 5.5 – Transitions probabilities of the matrix $M_{[14:00\breve{}17:00]}$

$$M_{[14:00\breve{}17:00]} = \begin{bmatrix} 0 & 0.20\ [60,180] & 0.60\ [60,180] & 0.15\ [60,180] & 0.05\ [60,180] \\ 0 & 0 & 0.10\ [60,120] & 0.70\ [60,120] & 0.20\ [60,120] \\ 0 & 1\ [60,120] & 0 & 0 & 0 \\ 0 & 0.35\ [60,120] & 0.35\ [60,120] & 0 & 0.30\ [60,120] \\ 0 & 0.33\ [60,120] & 0.33\ [60,120] & 0.34\ [60,120] & 0 \end{bmatrix}$$

5.6.2 Datasets Description

As discussed previously, our dataset (used in the evaluation of our monitoring approaches) is based on the pseudo variable-length Markovian model. We developed our scenarios using the Matlab environment. Our dataset describes the performances of the a monitored person, typically an elderly, regarding the achievements of his daily life activities. The scenarios, included in the dataset, involve sequences of activities achieved, during a whole year, by the elderly with different levels of dependency.

Our simulation strategy produces several scenarios either within the same person's profile (profile P_1) or with profile changes representing the person's loss of abilities. The representation of the experimental dataset involves different formats, codes, and names for actions and for high-level activities which are composed of atomic actions [295]. We simply the presentation and coding of an achieved activity using the following time series format: [*day's number*, *starting time*, *day's number*, *ending time*, *activity name*]. Table 5.5 shows an example of activities sequence.

In order to consider the activities (items) listed in the SMAF model and the five aspects of functional abilities of SMAF, our dataset includes most of the basic activities and related events such as *Eating* in the ADL class, *Meal preparation* in IADL class, and *Going outside* in mobility class of activities. Other items, such as *Hearing*, *Speaking* and *Memory* which are considered in the communication and mental functions classes, do not appear directly in our dataset. They are deduced based on the person's ability in performing the other activities (see Chapter 4) and using our relational approach. In sum, 22 high-level activities, describing the person's daily life behavior at home, have been considered in the dataset generation. A high-level activity can be composed of atomic actions required to correctly achieve the activity. Considered activities and actions are: Eating, Dressing, Washing, Grooming (washing hand/face, hair dry, and makeup actions), Toileting, Housekeeping, Laundry, Meal preparation (make coffee, make tea, make sandwich, make hot food, move dish, wash dish, etc.), Telephone use, Taking medication, Walk up/down, Walk in/out side, Watching TV, Reading, and Sleeping [295].

By applying the monitoring of one single person with different scenarios, we perform various experimentations and mainly focus on the adaptive monitoring issues. In our context-aware framework, it is assumed that the considered activities are easily identifiable by relying on the existed hardware infrastructure enriched by the techniques and knowledge of activity recognition [140, 161].

Table 5.5 – Dataset sequence example of activities of daily living

Day	**Start time**	**Day**	**End time**	**Activity**
09	08:10:39	09	08:30:32	Washing (take shower)
09	08:31:57	09	08:33:57	Hair dray
09	08:35:09	09	08:41:15	Change clothes
09	08:42:21	09	08:51:05	Toileting
09	08:52:55	09	08:57:34	Washing hand/face
09	08:58:55	09	09:06:39	Make coffee
09	09:08:27	09	09:13:41	Washing hand/face
09	09:15:02	09	09:20:16	Make sandwich
09	09:21:40	09	09:45:00	Eating
...	...	...	...	...
09	23:31:46	10	07:25:07	Sleep
10	07:27:59	10	07:35:00	Toileting

5.7 Experimentation Results

To show the ability of the adaptive monitoring, discussed earlier, we have conducted several simulations for the outcome of the person's behavior in terms of time series during one year. For the sake of simplicity and to focus on the adaptive monitoring issues, we perform our experimentations based on the monitoring of one single person. However, we note that the framework that we propose is not limited to the monitoring of a single person. Indeed, once the actor of a given activity is identified, the proposed approaches remain the same. The person's identification can be guaranteed using any kind of techniques such as RFID.

Our experimentations apply the previously discussed approaches used in Algorithm 4 using two different classes of scenarios. First, we consider the scenarios of an elderly having the same level of dependency and thus belonging to the same profile. The selected profile is the profile P_1 of the SMAF model which represents autonomous people or those with a lowest level of dependency. Secondly, we simulate the person's loss of abilities by considering changes in the person's profile and hence in the level of dependency. The considered profile changes are as follows: the person belong to profile P_1 during the first 3 months, then, profile P_3 from month 4 to 6, then profile P_6 from month 7 to 9, and finally he will belong to profile P_9 for the last three months of the year. We evaluate the optimization of our adaptive monitoring that reduces sensing data without compromising the credibility and reliability of the dependency evaluation and with the identification of abnormal situations that may cause a risk for the person. More specifically, our evaluations measure the computing process (number of monitored activities), the detection of abnormal situations, the energy, and network traffic consumption for a traditional (continuous) monitoring and then with our adaptive monitoring.

To strengthen the flexibility of our evaluation, we avoid rigid and restrictive settings specifically for the network traffic and energy consumption. Therefore, we consider the variation of three classes of sensor nodes: *high*, *medium*, and *low* used in the monitoring of the person's activities (Section 5.4.1). It is obvious that the resources consumption of the system depends on the nature of the sensors used to monitor a given activity. Table 5.1 gives the classes of different sensors that can be used in activities monitoring. For each considered class, we associate a metric function that returns the different consumption values. For instance, for the *low* class, we consider typical sensors with standard power values: 10.8mA, 7.5mA and 1μA in the transmitting, idle/receiving, and sleeping modes respectively [309].

Elderly persons' needs of assistance and services are changing gradually over the time. Therefore, the adaptation with these changes of the person's life over long-term are required in e-health systems.

However, this is not the only concern, indeed, it is of paramount importance to ensure a quick adaptation to sharp the sudden decline of the health status. Therefore, we consider different scenarios in our experimentations. First, the proposed adaptive system has been compared, during one year, with a continuous traditional system regarding the number of monitored activities. The results of this evaluation are shown in Figure 5.6.

As we can observe in Figure 5.6, we notice an increase in the monitoring of our system without profile changes (Figure 5.6-A) and with profile changes (Figure 5.6-B). In our evaluation presented in Figure 5.6-B, there are three declines of the health conditions with profile changes in the used scenarios: $P_1 \rightarrow P_3$, $P_3 \rightarrow P_6$ and $P_6 \rightarrow P_9$. The changes of profiles are: P_1 during the first 3 months, P_3 from the beginning of month 4 to month 6, P_6 from the beginning of month 7 to month 9, and profiles P_9 for the last three months.

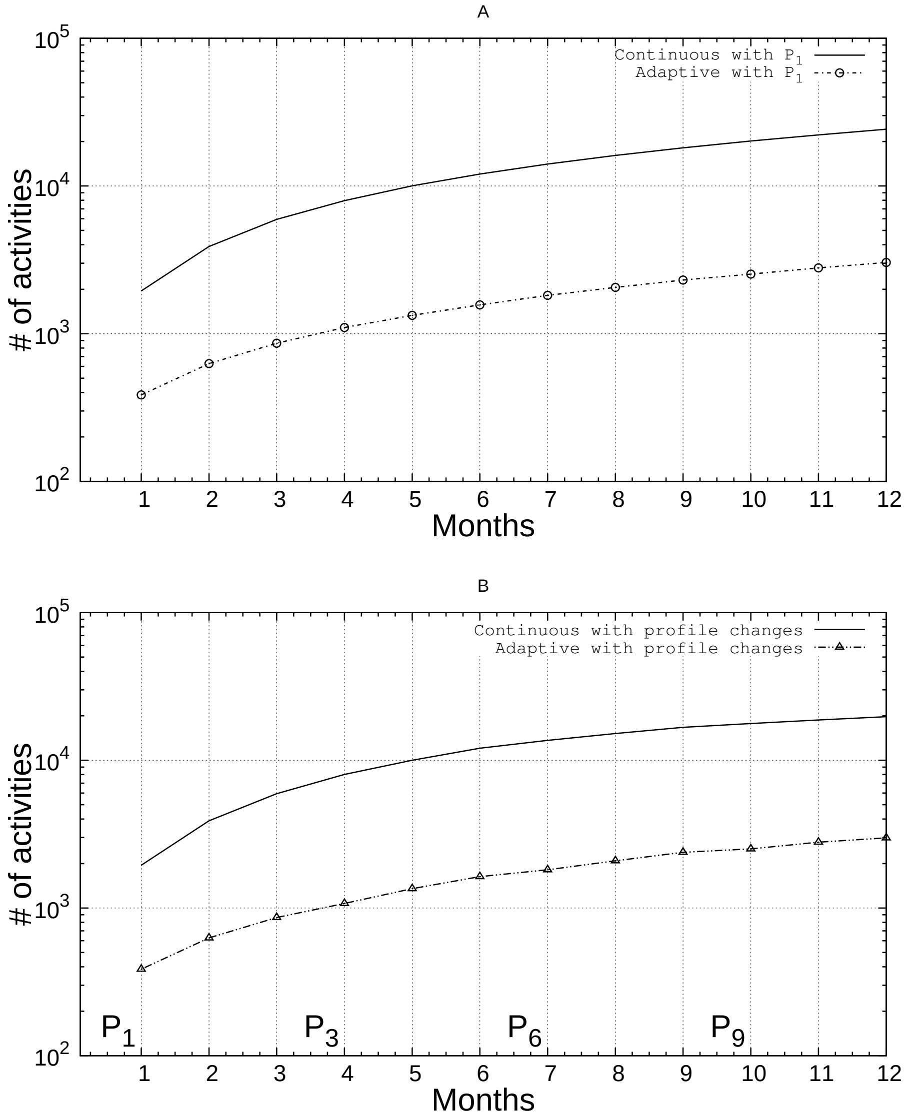

Figure 5.6 – Accumulated number of monitored activities

We observe a high accuracy of decline detection using our adaptive system. This is explained thanks to the consideration of the dependency level, the history of the behavior and the detection of abnormal situations while keeping a very low amount of sensed data. The results reveal that even with a declin of the health status, ensuring a timely and context-aware monitoring does not require sensing a huge amount of data. Indeed, our adaptive approach needs sensing only 15.12% (with profile changes) and 12.34% (with the same autonomous profile) of data compared to a traditional continuous monitoring scheme (Figure 5.6). Hence the proposed scheme leads to an important saving of energy and network traffic.

Figures 5.7 and 5.8 respectively compare the accumulated energy and network traffic consumption between the continuous and our adaptive monitoring within the same person's profile (P_1) and within profile changes. The observed gain is 90.2%

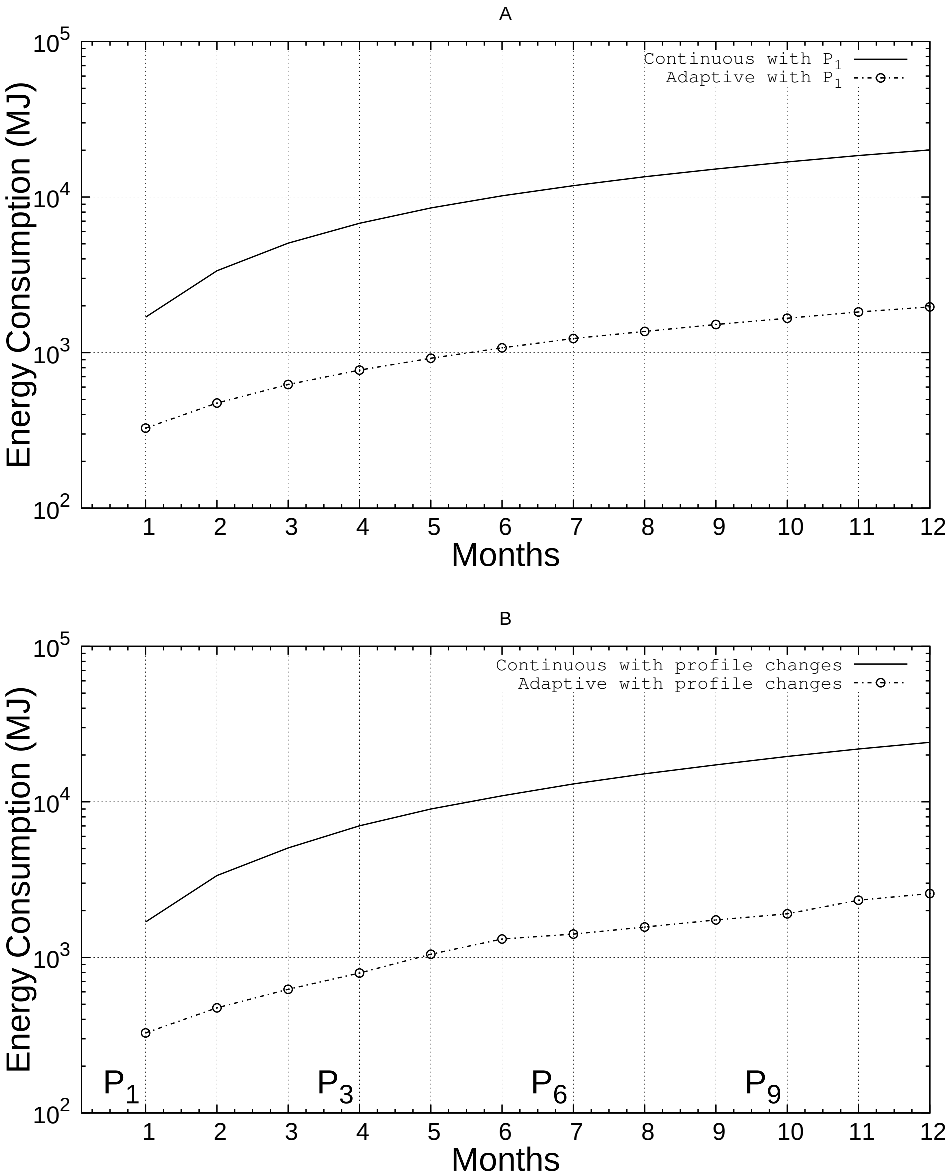

Figure 5.7 – Accumulated energy consumption

for the energy and 90.99% for the network traffic within the same person's profile, while a gain of 89.3% for the energy and 89.9% for the network traffic is observed within a person's loss of abilities (i.e. with profile changes). This observation is explained by the conditional monitoring that considers the nature of the activities and the person's profile, hence, no extra monitoring and data collection are used when it is not required.

For more readability, for each activity, Tables 5.6 and 5.7 show the percentages of saving (sensing activities, power, and network traffic) between the traditional continuous monitoring and our adaptive system in the same profile of persons (Table

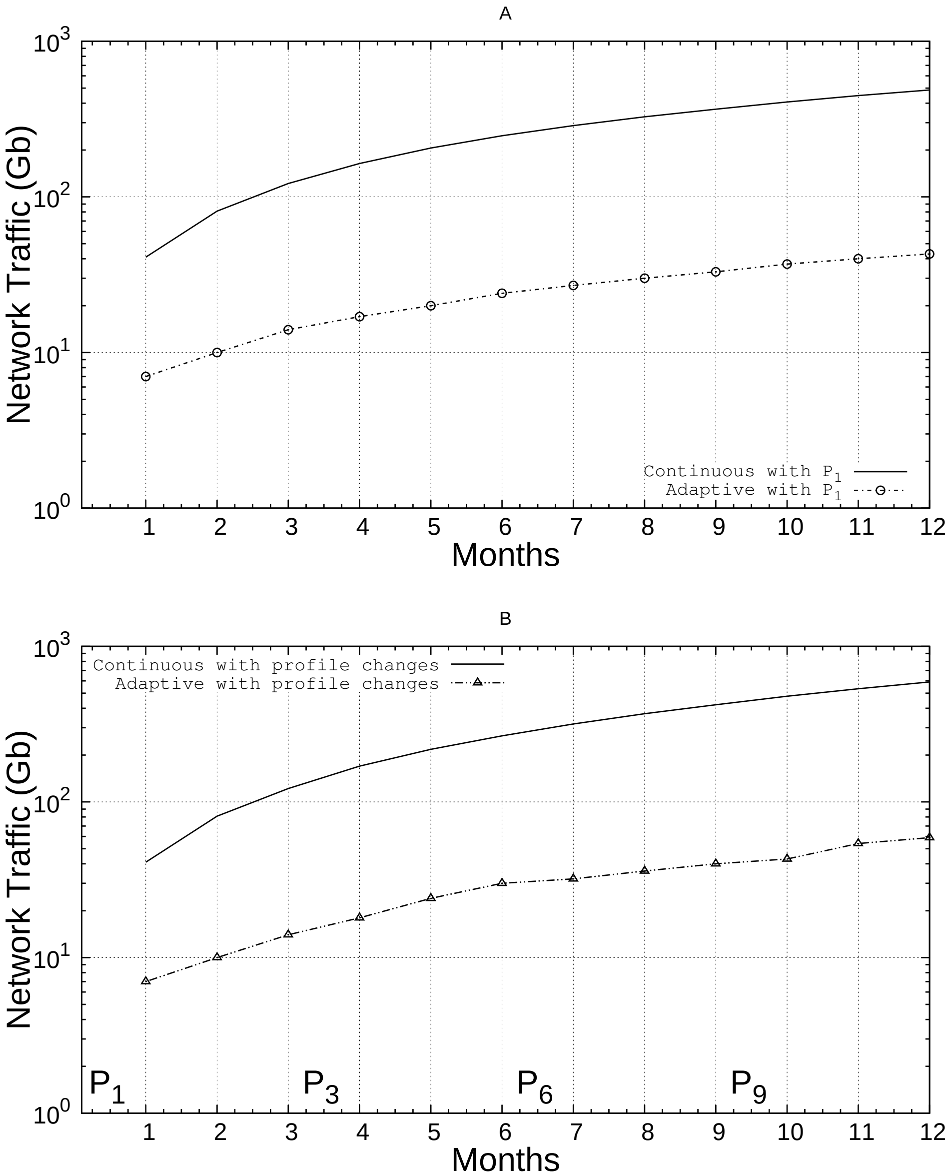

Figure 5.8 – Accumulated network bandwidth consumption

5.7) and with different profiles (Table 5.6). The results indicate that we saved 84.9% of sensing activities, 89.3% of energy, and 89.9% of network traffic within profile changes, and 87.5% of sensing activities, 90.2% of energy, and 91% of network traffic with a monitored person belonging to the same profile.

In addition to the observed significant optimization of resources, our adaptive approach succeeds to ensure a high accuracy (87.28%) for the detection of abnormal situations (Figure 5.9). In our evaluation, the abnormal situations are generated in the input scenario by associating the activities with particular values regarding durations (e.g. a very long or very short value for specific activities such as *Toileting*) and frequencies (e.g. a null value for some required activities such as *Eating* and

Table 5.6 – Comparison between the continuous and our adaptive monitoring system with changes of the person's abilities

	Sensing activities saving (%)	Power saving (%)	Network traffic saving (%)
Eating	93.9709	93.5675	93.5675
Dressing	98.8984	98.8179	98.8179
Washing	96.6292	96.9211	96.9211
Grooming	99.6508	99.6711	99.6711
Toileting	92.6705	92.6022	92.6022
Housekeeping	30.7692	32.3409	32.3409
Laundry	76.9231	76.4868	76.4868
Meal preparation	48.7549	54.9485	54.9485
Telephone use	95.7983	N/A	N/A
Medication use	65.2174	65.4096	65.2174
Watching TV	96.8077	96.6794	96.6794
Reading	88.8601	86.1941	86.1941
Sleeping	66.0952	61.3398	63.2381
Weight	98.8571	98.8571	98.8571
Walking inside	81.8147	N/A (computed)	N/A (computed)
Total	84.8809	89.3315	89.8829

Table 5.7 – Comparison between the continuous and our adaptive monitoring system with the same person's profile

	Sensing activities saving (%)	Power saving (%)	Network traffic saving (%)
Eating	97.3001	97.3476	97.3476
Dressing	99.6700	99.6115	99.6115
Washing	99.1620	99.0951	99.0951
Grooming	99.9072	99.8963	99.8963
Toileting	97.6500	97.6574	97.6574
Housekeeping	29.4118	30.8033	30.8033
Laundry	94.1176	94.1020	94.1020
Meal preparation	66.7587	66.3693	66.3693
Telephone use	99.5757	N/A	N/A
Medication use	66.6667	66.7163	66.6667
Watching TV	99.7479	99.7369	99.7369
Reading	98.8679	98.7175	98.7175
Sleeping	66.2890	65.1487	66.2890
Weight	98.8669	98.8669	98.8669
Walking inside	85.0883	N/A (computed)	N/A (computed)
Total	87.4659	90.2038	90.9906

Medication use). Notice that the observed accuracy of 87.28% represents an average and includes the period when the person is almost autonomous (i.e. from the first to the third month) where abnormal detections includes false alarms. The accuracy in detecting abnormal situations tends towards 100% when there is a serious loss of the person's abilities, especially starting from month 8 (Figure 5.9). This result confirms the efficient adaptability of our approach.

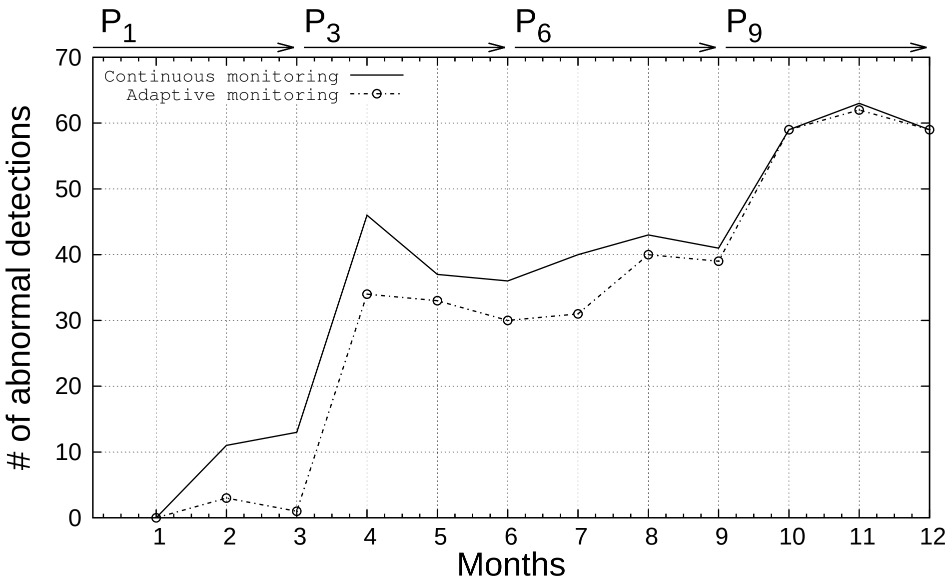

Figure 5.9 – Detection of abnormal situations when the person's profile changes

In order to evaluate the adaptability of our approach, we also compare the cost of our adaptive approach with two scenarios: within the same level of dependency and with profile changes (Figure 5.10. Notice that in spite of increasing the monitoring frequency when the dependency level increases, the observed number of monitored activities using our approach is almost the same with or without profile changes, see Figure 5.10-A. This is simply explained by the fact that the person achieves a reduced number of activities when he starts loosing its abilities.

5.8 Conclusion

To face the growing demand for e-health monitoring systems for vulnerable individuals especially elderly and dependent persons, the design of an efficient adaptive and context-aware system becomes necessary. Such systems monitor the person's activities of daily living and provide required help and assistance especially when risk and abnormal situations occur.

The contribution of this Chapter addressed the proposition of a new context-aware adaptive framework for monitoring the activities of daily living. The framework tackles the drawback and weakness of existing e-health solutions and provides an efficient monitoring that optimizes the system resources. The aim was to improve the effectiveness of existing e-health monitoring schemes while maintaining a strong link with existing medical methods, such as the models used in the geriatric

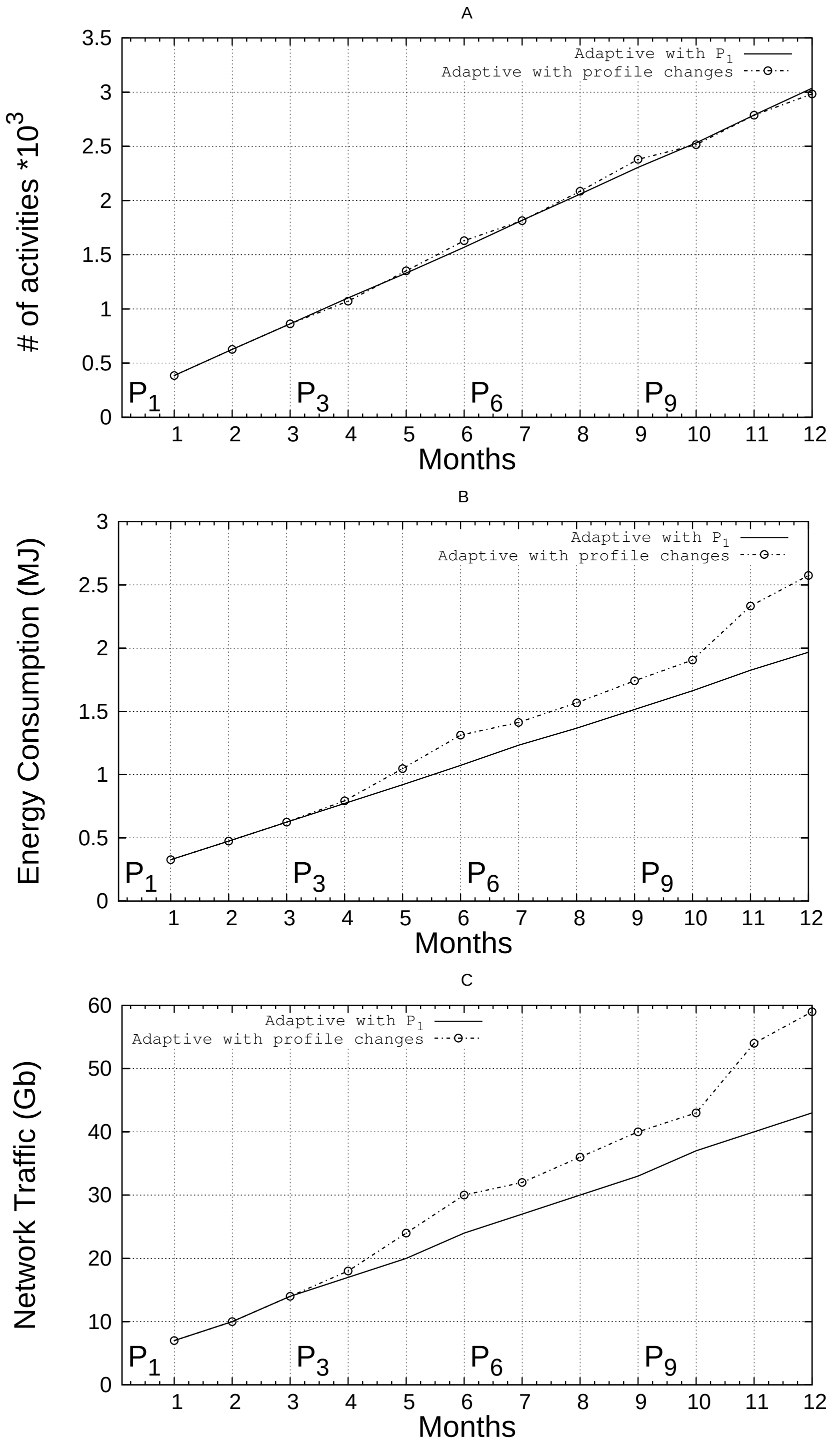

Figure 5.10 – Consumption with and without profile changes

domain. We targeted providing a monitoring which is dynamically adapted to the context and situation of the monitored person, his history, the nature of monitored activities, and the existing relationships between activities.

This efficiency of our framework is ensured thanks to the defined conditional monitoring and processing, considering the person's profile to dynamically determine the frequency of data sensing, automatically evaluating the dependency, using abnormal behavior detection, and power saving. The definition of a pseudo variable-length Markovian model has allowed to generate long-term realistic scenarios that can be used for real-life testing and implementations with a high flexibility. Our different experimentations covering, each time, one year of monitoring data, has shown that our adaptive context-aware monitoring system identifies the context of the person with a high accuracy (87,28% of accuracy and more for severe dependency situations) with a minimum amount of sensing data. The proposed adaptive approach required a sensing of only 15.12% of data (when the person's abilities change) and 12.34% of data (with the person belongs to the same profile) compared to the traditional continuous monitoring scheme. Moreover, the proposed framework was able to sense data with a high flexibility while reducing the energy consumption (by 90.99%) and the network bandwidth use (by 90.2%) within persons in the same level of dependency and reducing 89.3% of the energy and 89.9% of the network traffic within a person facing a loss of abilities.

CHAPTER 6

Health State Prediction and Behavioural Change Detection

Contents

6.1 Introduction

Context-aware healthcare and assisted living systems target the monitoring and evaluating the person's functional abilities regarding the correct achievement of the ADL activities. Such systems are effective when they succeed to gain a good knowledge of the human's daily behavior and become able to understand the normal behavior, detect abnormal situations, and predict future health conditions. In real life, the human's behavior is highly dependent on perception, context, environment and prior knowledge. Furthermore, there are other important factors that can affect the behavior such as the physical and mental conditions and human changes such as those related to the perceptual abilities, physical skill, and memory. Therefore, a key challenge in a smart systems is to define appropriate techniques that can effectively understand the complex and variable human behavior and predict the health state related to the future achievement of daily activity.

Most of the recent studied researches tackle these common set of challenges and suffer from similar limitations. Mainly, we cite the lack of methods that detect the abnormalities and the use of prediction techniques that requires a long training time, the analysis of a huge amount of data, and the need to perform a continuous monitoring all the time whatever the person's context. Therefore, there is an urgent need to design an efficient system combining an optimal monitoring cost with an accurate prediction of the person's behavior.

In this Chapter, we propose a predictive and context-aware e-health monitoring in smart environments. The objective of the proposed approach is to ensure efficient sensing frequencies and combine a good optimization of the resources with a good credibility in evaluating the dependency of monitored persons. The optimization of resources concern many dimensions like computing (collect relevant and contextual data), network traffic and energy consumption. Moreover, our goal is to provide a high accuracy for detecting the abnormal and unusual situations for all the levels of the person's dependency. Our contribution targets gaining the ability to extract and predict future health condition of persons. The approach is based on a good knowledge of the person's behavior and the usually observed energy consumption for each activity with a need of only short training periods and a minimum amount of sensed data.

The layout of this Chapter is organized as follows: the methodology of the proposed monitoring is presented in Section 6.2. The forecasting model and behavior changes detection are described in Section 6.3. In Section 6.4, a new monitoring algorithm is discussed. In Section 6.5, the performances of the proposed monitoring scheme are evaluated and compared to traditional monitoring approaches within different scenarios and persons' profiles. The conclusions of this Chapter are drawn in Section 6.6.

6.2 Methodology

Health monitoring systems should take into consideration several factors for an efficient monitoring and evaluation of persons. Mainly, we identify these factors as those related to the person's health condition including the person's level of dependency, the regular and periodic human behavior, the health history and the techniques that can be defined and applied in order to predict the evolution of the person's health.

These factors are directly related to the ability of persons to achieve the main activities of daily living such as $Eating$, $Toileting$, $Mealpreparation$, etc. Sensing such activities, using the hardware and software resources of the smart environment, should be tied to the nature of the monitored activity, its repeatability, the duration required to achieve a given activity by the monitored person, and the direct impact of the monitoring system on the lives of individuals. Consequently, for an efficient monitoring, the sensing frequencies should be dynamically updated based on the identified factors and influenced by the detection of the abnormal and unusual behavior of the monitored subjects.

In this Chapter, our objective is to come up with an efficient monitoring system based on (1) the use of optimal sensing frequencies for each activity, (2) a dynamic update scheme of sensing the activities, and (3) the prediction of the person's behavior in order to guide the deployed sensors for an optimal monitoring. We propose a predictive context-aware system that uses the conditional processing scheme (Figure 5.2) which was presented in the previous Chapter. In this system, the person's profile which includes the dependency level and historical records, represent the essential key to motivate the sensor nodes for an optimal sensing in order to enable the processing of highly relevant data. Consequently, the proposed approach deals with the necessity of data collection by learning the human behavior, evaluating the health condition, and predicting the future behavior all that with a dynamic update of the person's activities monitoring.

In order to reach our objective and to model the complex human behavior using realistic and adaptable models, the adaptive and predictive context-aware monitoring system uses two approaches: the *evaluation of activities* approach and the *dynamic monitoring* approach. It is worth mentioning that these two approaches are similar to those discussed in the previous Chapter (Sections 5.4.1 and 5.4.2) with are improved in this contribution.

6.2.1 Evaluation of Activities

Based on the nature of each activity and the required time to monitor it, the activities are associated with a set of dynamic information such as the frequency (i.e. when to monitor?), duration (how long to monitor?), and scores to determine the monitoring mode to be applied. The activities are classified into two main categories of monitoring: *Category I* and *Category II*. In *Category II*, the initial monitoring frequency (i.e. the x value) can be one of the different values: 1, 2, or 3. The monitoring duration is 24 hours. For example, for a given activity, if x is fixed to 2, this means that the system triggers a new monitoring each 2 days. In *Category I*, if the selected frequency (i.e. the x value) is 3 and the duration is *always active* till the activity occurs, so the next round of the monitoring is triggered after the x value which menas, here, 3 days.

Like the in the approach discussed in Section 5.4.1, if the system monitors, for instance, the *Toileting* activity each 2 days during 24 hours, the monitoring leads to a total number of 15 results during a one month (i.e. P=30 days). Each single result of the calculated 15 results refers to the person success/fail in performing the monitored activity. The variable *activityResults* represents the number of activities performed correctly. The obtained results are used to progressively evaluate the person's ability to achieve an activity within the determined duration. A monitoring duration is tailored to each activity. Recall that we defined four scores which are $Autonomous(A)$ (0), $Supervision(S)$ (-1), $Needhelp(H)$ (-2), and $Dependence(D)$ (-3). As discussed previously, the monitoring result of each activity is evaluated using four intervals with a step of $P/4.x$, where x is the sensing frequency and P is a period of time (duration) used to re-evaluate the person's dependency. For example, if we have a positive monitoring result for a given activity which is $activityresults = 10$, a x value of 2 with a P=30, then the used score intervals are $D \equiv [0, step{=}3.75[$; $H \equiv [step{=}3.75, 2.step{=}7.5[$; $S \equiv [2.step{=}7.5, 3.step{=}11.25[$ and $A \equiv [3.step{=}11.25, 4.step{=}15]$. Consequently, since $activityresults = 10$, the monitored activity, in this example, is evaluated S which means that the person needs *supervision*.

Unlike the approach discussed in Section 5.4.1 of the previous Chapter, in which the system checks the person's behavior with the previously observed average. Here, the system checks the person's behavior with *predicted* values. If the performed activities are lower or higher than the predicted values (mainly in terms of number and duration), the system will detect an abnormal behavior and extends the monitoring for an extra duration period. Otherwise, the system will count the single observed result, if the observed number (at the end of duration) is greater than or equals to a predefined value. For instance, for the *Toileting* activity, if there is no detected abnormal behavior and the observed number is greater than or equal to 2, the single result will be considered.

6.2.2 Dynamic Monitoring

An optimal ecosystem of health monitoring has to determine the degree of data sensing (i.e. frequency) in order to avoid unnecessary data and the exaggerations of the existing dependency models as we presented in Chapter 4. Therefore, to optimize the monitoring mode, we opt for the person's dependency evaluation as an essential key to increase or decrease the frequency of the monitoring mode. The idea is to provide a dynamic frequency of monitoring by updating the initial x value (discussed previously) according to the person's dependency level and by using one of the existing evaluation models in the geriatrics domain. Table 6.1 shows our system's dynamic updates of the x frequency regarding a given person's profile, which is periodically evaluated. As we can observe, the selected frequency, x, is related to the type of the monitored activity and depends on the current profile of the monitored person. Thus, the monitoring can be increased, decreased or even stopped.

6.3 Prediction of the Person's Behavior

Time is the key dimension in the person's daily routines. It reflects the most important contextual dimensions for a context-aware e-health monitoring system. The monitoring and evaluation of daily activities performances highlight the behavior of the person and leads to the ability for a given system to detect any abnormality or change in the behavioral patterns.

Changes related to the daily activities performance can be determined with respect to durations, frequencies, and absence of activities. The regular and normal behavior of a monitored person can be observed based on the durations and frequencies used in performing the different activities. If any real deviation in the behaviors, compared to the norm, is observed, an irregular situation is detected. Despite the unstable intraday behavior of persons and the uncertainty of their environment, data series including the person's history help the system to efficiently expect and forecast future behaviors.

Table 6.1 – Dynamic monitoring mode

	ADL	Mob.	Com.	M.F.	IADL
P_1	$x = x/1$ (initial x)	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/1$
P_2	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/1$
P_3	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/2$
P_4	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/2$
P_5	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/3$
P_6	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/3$
P_7	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/2$	$x = x/(3-1)$
P_8	$x = x/1$	$x = x/1$	$x = x/1$	$x = x/2$	$x = x/(3-1)$
P_9	$x = x/2$	$x = x/2$	$x = x/1$	$x = x/1$	$x = x/(3-2)$
P_{10}	$x = x/2$	$x = x/1$	$x = x/1$	$x = x/2$	$x = x/(3-2)$
P_{11}	$x = x/2$	$x = x/2$	$x = x/1$	$x = x/2$	$x = inf.$
P_{12}	$x = x/3$	$x = x/2$	$x = x/1$	$x = x/2$	$x = inf.$
P_{13}	$x = x/3$	$x = x/3$	$x = x/1$	$x = x/2$	$x = inf.$
P_{14}	$x = x/3$	$x = x/3$	$x = x/2$	$x = x/3$	$x = inf.$

Autonomy, Difficulties, Supervision, Help, Dependence [5]

To reach the goal of sensing high relevant data of the person's context, we propose a predictive model based on the Grey model theory [310]. The objective of our model is to learn the behavioral patterns with the minimum set of relevant data. The model, that we propose, ensures a prediction of the health conditions of persons based on the observed behavior and using the knowledge related to person's energy consumption for each activity in order to detect abnormal situations. Consequently, by only using relevant data, the system provides a proactive attention and can trigger notifications to caregivers if a high probability of decline is detected.

6.3.1 The Forecasting Model

The Grey model (GM) is a widely used model for the prediction of systems coming with incomplete information and uncertain concepts. The model represents an efficient and adapted tool that can be applied using only short training (learning) periods. The Grey model, GM (n, h), uses n-order differential equations and a set of variables where its cardinal is h. The single variable first order model GM (1,1) is a time series forecasting model that we adopt to learn and predict the person's behavior trend, i.e., the increasing or decreasing level of dependency. GM (1, 1) is summarized as follows [310].

The system considers an initial non-negative time sequence of data $X^{(0)}$ where

$$X^{(0)} = \{x^{(0)}(1),\ x^{(0)}(2),\ ..,\ x^{(0)}(n)\} \tag{6.1}$$

Based on the initial sequence $X^{(0)}$, a new sequence $X^{(1)}$, called accumulated sequence, is generated by applying the accumulated generating operation (AGO) in order to smooth the randomness.

$$X^{(1)} = \{x^{(1)}(1),\ x^{(1)}(2),\ ..,\ x^{(1)}(n)\} \tag{6.2}$$

Where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \quad 1\ \leq k\ \leq n \tag{6.3}$$

The generated mean sequence $Z^{(1)}$ is derived from $X^{(1)}$ using the mean value of each two consecutive terms.

$$Z^{(1)} = \{z^{(1)}(2),\ z^{(1)}(3),\ ..,\ z^{(1)}(n)\} \tag{6.4}$$

Where

$$z^{(1)}(k) = \frac{1}{2}x^{(1)}(k) + \frac{1}{2}x^{(1)}(k-1), \quad 2\ \leq k\ \leq n \tag{6.5}$$

The first order differential equation of GM (1, 1) is defined as follows:

$$x^{(0)}(k) + az^{(1)}(k) = b, \quad 2\ \leq k\ \leq n \tag{6.6}$$

Thus, the whitening equation is:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{6.7}$$

Let Y and B be:

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{6.8}$$

The a and b parameters can be found as follows:

$$[a, b]^T = \left(B^T B\right)^{-1} B^T Y \tag{6.9}$$

According to the whitened equation of GM (1, 1), the solution of $X^{(1)}$ at time k is:

$$x_p^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right]e^{-ak} + \frac{b}{a} \tag{6.10}$$

Consequently, to obtain the predicted value of the initial data row at time $(k+1)$ we use

$$x_p^{(0)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right]e^{-ak}(1 - e^{a}) \tag{6.11}$$

For all the considered activities, we calculate the predictive values (durations and frequencies) by applying the previous model on the initial data sequence, which is represented by the observed values during the monitoring of the person. Algorithm 6 presents an example of prediction about the required duration of activities. Initial data include the sequence of durations that were used, by the person, to achieve the daily activities. If the data raw size is very small (less than 3), the system considers the previously observed durations. Otherwise, the Grey model is applied to predict next values. Figure 6.1 shows an example of current observations and the predicted trend using GM(1,1). The example considered the *Toileting* activity in terms of durations and frequencies (i.e. the number activities performed correctly). Figure 6.1-A represents the actual (observed) and predicted trend of durations used in achieving the activity during two months. Figure 6.1-B represents the actual and trend number (i.e. frequencies) of the achieved *Toileting* during three months.

Algorithm 6 Values prediction using GM(1, 1)

function GreyModel(*durationBehavior(act)*)
  $X^{(0)} \leftarrow \{x^{(0)}(1),\, x^{(0)}(2),\, ..\, ,\, x^{(0)}(n)\}$.
  ▷ *initial data sequence*
  if $n < 3$ **then**
    $x^{(0)}(n+1) \leftarrow x^{(0)}(n)$
    return *predictedDuration(act)*
  else
    $X^{(1)} \leftarrow \text{AGO } X^{(0)}$.
    $[\text{a,b}]^T \leftarrow \left(B^T\ B\right)^{-1} B^T Y$.
    ▷ *compute B and Y*
    ▷ *Grey tries to find an estimation of "a" and "b"*
    $x_p^{(0)}\ (k+1) \leftarrow \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak}(1\text{-}e^{a})$
    ▷ *compute a predicted value*
    return *predictedDuration(act)*
  end if
end function

6.3.2 The Detection of Behavior Changes

Using a minimum amount of sensed data and short training periods, our proposed monitoring system categorizes the behavior of the monitored persons as either normal (regular) or abnormal (irregular). After the determination of the standard deviation σ of the observed values and the Grey values using Eq. 6.11, we get a range of forecast between a lower limit (minimum) and upper limit (maximum) where the lower limit is *Grey value* - σ and the upper limit is *Grey value* + σ. Durations and frequencies for each activity are checked with the min/max ranges of forecast.

A given situation is considered as a *normal behavior* if the observed values for the activity (i.e., duration and frequency) fit with the forecasting range:

$$[Greyvalue - \sigma, Greyvalue + \sigma]$$

Otherwise, the observation is categorized as an anomalous situation. It is worth noting that the combination of the standard deviation (SD) with GM (1, 1) values

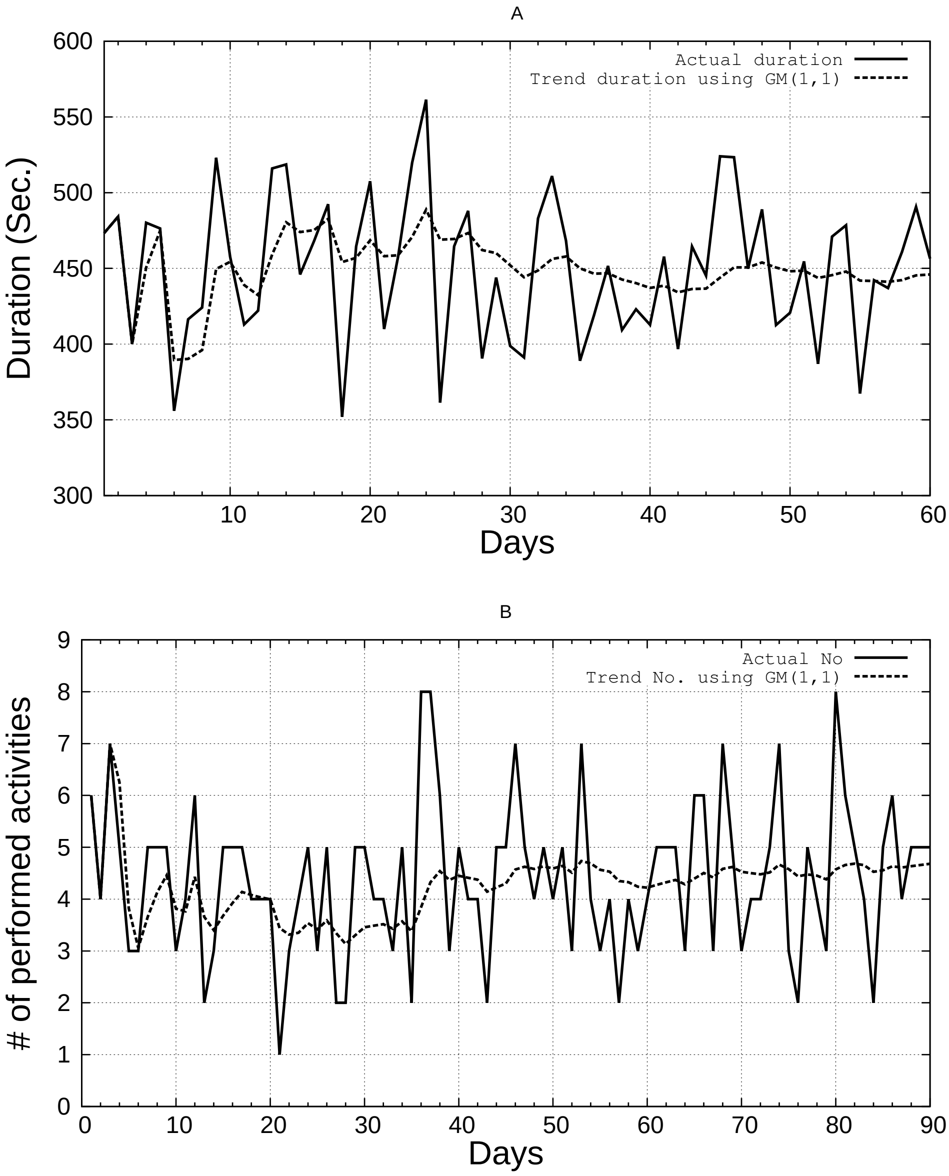

Figure 6.1 – Observations and predictions, using GM(1,1), for the *Toileting* activity

represents a good indicator for the detection of the behavior changes. Unfortunately, this indicator is not enough to judge if a behavior change represents a real abnormal situation or not. Indeed by relying only on SD, some normal situations could be considered as abnormal when they are compared to the majority of observed values. Similarly, some real abnormalities can be ignored if they occur among a series of abnormal values. Indeed, unlike expert data, SD values depend only on the comparison of input values for a given observed scenario whatever the kind of the performed activity. Expert data are based on medical knowledge and experiments that identify the real risks which, of course, depends widely on the nature of the human activity. Consequently, input expert data (e.g. those coming from health professionals) are needed during the setup of the system in order to moderate the SD impact. These inputs enrich the system with the ability to determine if a detected change represents really an abnormal situation that could be dangerous for the monitored person.

6.4 Monitoring Algorithm

Based on our proposed methodology and used forecasting model, the proposed algorithm simulates data series with time evolution (variable i) using different input scenarios generated for one year (Algorithm 7, line 3). All the considered activities (Categories I and II, see Section 6.2.1) have a monitoring time ($MTime$) depending on the sensing frequency (the x value). The x value varies according to the nature of monitored activity and the monitoring mode. The x value is updated regularly based on the evaluation of person's context (profile). To evaluate the person's state, we use the scores associated to different activities (Algorithm 7, lines 11, 22 and 38). It is worth repeating that, scores are tested with the four modalities: A, S, H and D as we can see in the *SMAFScore* function (line 50). The person's profile is then computed using the *computeSMAFProfile* function (line 52). The determined person's profile determines the new x value and monitoring time ($MTime$) for each activity (line 53) using the *DynamicMonitoring* procedure. Without long training time and even with data sequences that are incomplete, our algorithm starts to approximate the behavior of the daily life and predict next values. For this purpose, we mainly use the duration and repeatability in achieving the different activities (see *Duration*() and *actNumber*() functions in Algorithm 7, lines 10 and 34 for instance). When the observed and predicted behavior are similar, the regular and continue monitoring mode remains unchanged (lines 12 and 39). Otherwise, the system detects abnormalities (lines 15, 24, and 36) and applies a new mode of continuous monitoring (lines 14, 32, and 35). The new mode is stopped once the behavior becomes as usual. As we can notice, the proposed algorithm relies on predictive functions that use many factors such as durations, repeatability and power consumption required by the activities. As presented before, Algorithm 6 gives an example of values prediction regarding the duration used in performing the person's activities.

6.5 Experimental Results

In accordance with the discussed approaches and forecasting model used for an efficient context-aware monitoring, we conducted various experiments to evaluate the proposed system in the terms of (a) experimenting the validity of the monitoring and its adaptability, (b) the efficiency of sensing frequencies selection, and (c) the performance and accuracy of the prediction regarding the evolution of the person's conditions.

To show the ability of the adaptive monitoring and the predictive model discussed earlier, we performed simulations for the outcome of the person's behavior in terms of time series during one year. Our experimentations apply the discussed approaches used in Algorithm 7 using two different classes of scenarios, dataset generated synthetically (see our scenario generation strategy in Section 5.6). First, we

Algorithm 7 Adaptive & predictive context-aware monitoring

```
procedure AdaptivePredictiveMonitoring
    A ← activities; N ← year in seconds;
    act ← readLine(inputScenario); MTime(a_i) ← 0;
                    ▷ start reading activities & initialize "monitoring time" for all activities
    for i = 1 → N do                              ▷ i is the current moment of time evolution
        if i == startingTime(act) then
            switch act do                                              ▷ see Section 6.2.1
                case Category I :
                    if i ≥ MTime(act) then
                        compute network traffic and power consumption;
                        if Duration(act) satisfies PredictDur(act) then
                            activityResults(act)++;
                            updates MTime(act);
                        else
                            ContinueMTime(act);
                            abnormalDetection(act)++;
                        end if
                    end if
                case Category II :
                    if i ≥ MTime(act) and i ≤ MTime(act) + 24h then
                        compute network traffic and power consumption;
                        if Duration(act) satisfies PredictDur(act) then
                            temporaryactivityResults(act)++;
                        else
                            abnormalDetection(act)++;
                        end if
                    end if
            act ← readLine (inputScenario);
        end if
        for each a in Category II do
            if i ≥ MTime(a) + 24h then
                if abnormalDetection(act) > 0 then
                    ContinueMTime(act);
                else
                    if actNumber(act) ¬ satisfies PredictActNum(act) then
                        ContinueMTime(act);
                        abnormalDetection(act)++;
                    else
                        computeactivityResults (a);
                        updates MTime(a);
                    end if
                end if
            end if
        end for
        if mod (i, 1 days) == 0 then
            compute durbehavior (act) and no.behavior(act);
            Predictpower(act) ← GreyModel(power(act));
            PredictDur(act) ← GreyModel(durbehavior(act));
            PredictActNum(act) ← GreyModel(no.behavior(act));
        end if
        if mod (i, 30 days) == 0 then
                                        ▷ compute the activityScore (see Section 6.2.1)
            for l = 1 → A do
                activityScore(a_l) ← SMAFScore(activityResults(a_l));
            end for
            profile ← computeSMAFProfile(activityScores);
                                        ▷ for computing the SMAF score, see Chapter 4
            DynamicMonitoring(profile);
        end if
    end for
end procedure
```

consider scenarios of a person having the same level of dependency and thus belonging to the same profile. The selected profile is P_1 of SMAF which represents a person who is autonomous or with a low level of dependency. Secondly, we simulate the person's loss of abilities by injecting changes in the person's profile and hence by varying the level of dependency. The considered changes are: profile P_1 from month 1 to 3, profile P_3 from month 4 to 6, profile P_6 from month 7 to 9, and finally profile P_9 from month 10 to 12.

In addition to the objective of reducing the data sensing without compromising the reliability of dependency evaluation, the proposed monitoring system forecasts the person's behavior and health status and ensures the identification of abnormalities that can be dangerous for the person. The monitoring efficiency is evaluated by considering the computing process which is related to the number activities that are monitored by the system, the detection of abnormal situations, the dependency level, and the energy and network traffic consumption. We perform a comparison between the traditional systems (using an unconditional and continuous monitoring) and our adaptive and predictive monitoring. We consider the same three classes of sensors as used in Chapter 5: *high*, *medium*, and *low*.

6.5.1 Validation of the Adaptive Monitoring Approach

We conducted simulations with varying the sensing frequency (i.e. x value) in order to ensure and identify the efficient adjustment of frequencies that combines the optimization of the resources (computing, network and energy), the dynamic update of the monitoring mode (increase or decrease of x based on the health conditions), the credibility of dependency evaluation, and the guarantee of a high accuracy in the detection of abnormal and unusual situations whatever the level of the dependency.

In this contribution, identified values are used with the GM (1, 1) model in order to predict the health conditions based on the observed behavior and used energy. The first obtained results are presented in Table 6.2 where we show the saved percentages related to the sensing of monitored activities and the power and network traffic required by our adaptive system when it is compared to those required in unconditional continuous monitoring. A variation of the monitoring frequencies x (using X_1, X_2, X_3, and X_3) is applied on input scenarios which denote a person who belongs to the same profile P_1 of the SMAF model.

With X_1, all the considered activities (i.e. Categories I and II, see Section 6.2.1) are monitored with the same sensing frequency which refers to a maximum monitoring performed each day. With X_2, the used frequency (i.e. the x value) is set to 1 for Category II, and set to 3 for Category I. Using X_3, the x value is set to 2 for Category II, and to 5 for Category I. Finally, X_4 refers to the minimal monitoring, hence the x value is set to 3 for Category II and to 10 for Category I.

Thanks to the observed significant optimization, the proposed system succeeds to gain a perfect accuracy (100%) for the evaluation of person dependency level. The observed results, presented in Table 6.2, are mainly due to the conditional monitoring and its strong link to the person's profile and nature of activities. Hence, extra monitoring and data collection are avoided when it is possible.

By nature, the needs of elderly persons in terms of assistance and services are

Table 6.2 – Resources consumption of the adaptive monitoring (with different frequencies) compared to a continuous monitoring

X values	Sensing activities(%)	Power (%)	Network traffic (%)	Profile evaluation
X_1	60.82	66	65.05	P_1
X_2	54.02	55.38	54.12	P_1
X_3	30.48	30.70	29.99	P_1
X_4	21.49	20.96	20.40	P_1

changing gradually over the time. Therefore, to face the changes of the person's life over long-term the e-health systems must be adaptable. Moreover, it is of paramount importance to guarantee an adequate monitoring that sharps a possible sudden decline regarding the health status. In order to evaluate the adaptability of our approach and test the sensing frequencies, we compare the continuous monitoring and our monitoring system with a set of different x. The used scenarios consider declines of the person's health status. Specifically, three declines, represented by an ordered profile changes, are used: P_1, P_3, P_6, and P_9. It is worth repeating that the first profile P_1 represents autonomous persons and that the person's dependency increases when the profile increases. Figure 6.2 presents the required amount of resources in terms of computing, network, and power and shows the accuracy of the automatic dependency evaluation. In this Figure 6.2, the adaptive monitoring is applied, during 12 months, in different modes using X_1, X_2, X_3 and X_4 frequencies. The decline is represented by the change of the SMAF profile of the person from P_1, to P_3, then to P_6, and finally to P_9.

From Figure 6.2-A, we observe that our monitoring system performs a sensing of 61.5% of activities with $X1$, 54.3% with $X2$, 35.6% with $X3$, and 24.5% with $X4$ when compared to a traditional continuous monitoring scheme. Although the sensing of a very low amount of data, we observe a high accuracy related to the decline detection. This is mainly due to the consideration of the person's context. Specifically, the dependency degree and the history of the behavior. Consequently, due to the conditional monitoring that relies only on relevant sensed data, the observed gain is of 37.2% for the energy consumption and 38% for the network traffic with $X1$, 48.3% for the energy and 49.3% for the network traffic with $X2$, 64% for the energy and 64.6% for the network traffic with $X3$, and 74% for the energy and 74.3% for the network traffic with $X4$ (Figure 6.2-B and 6.2-C).

6.5.2 Validation of the Adaptive Monitoring with Prediction

As discussed in Section 6.3, our proposed predictive model is mainly based on time series analysis. We apply this model on our dataset in the same way as in the adaptive monitoring approach. In such a way, the used scenarios consider either person with the same level of autonomy or a person with a change regarding his abilities in performing the activities of daily living. The sensing frequencies

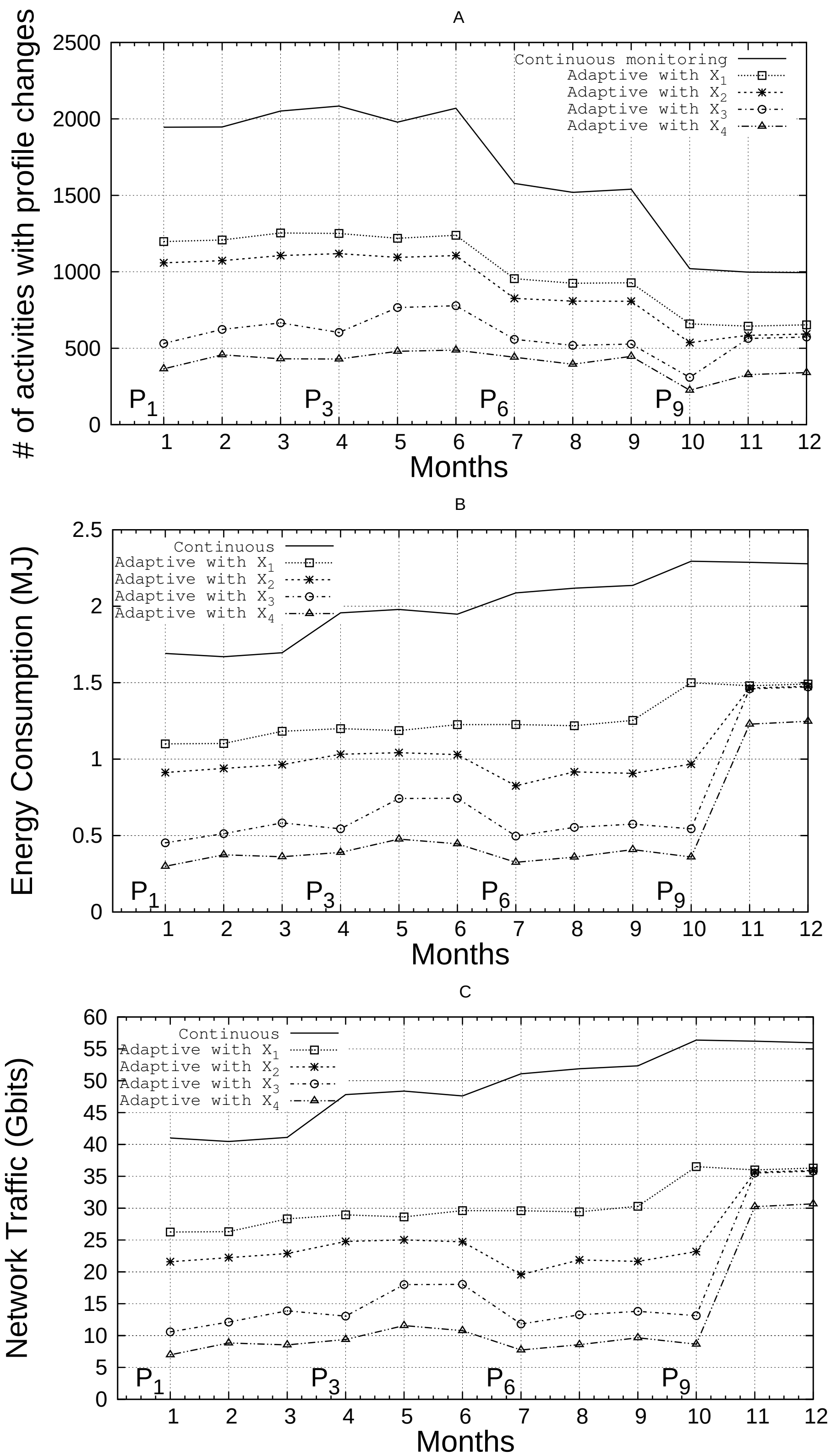

Figure 6.2 – Resources consumption in continuous and adaptive monitoring with health decline. (A) number of monitored activities, (B) energy consumption, (C) network bandwidth consumption

Table 6.3 – Resources consumption of the adaptive & predective monitoring (with different frequencies) compared to a continuous monitoring

X values	Sensing activities(%)	Power (%)	Network traffic (%)	Abnormal detection (%)	Profile evaluation
X_1	60.82	66	65.05	100	P_1
X_2	54.02	55.38	54.12	100	P_1
X_3	35.43	34.46	33.82	77.78	P_1
X_4	26.22	23.93	23.43	56	P_1

addressed previously are varied in the evaluation of the whole system. The goal of the prediction functionality is to provide the system with the ability to detect when a change occurs. Changes refer to how the monitored person performs the daily activities and also how to predict the future behavior based on previous and current situations. The used GM (1, 1) model helps to optimize the monitoring system by giving a more accurate map about the person's context. It is the context which allows the identification of an abnormal behavior, hence, it is required to have a higher data sensing compared to the adaptive approach. A robust context-aware monitoring system can be evaluated based on how much it can afford a good vision and knowledge of the person's context and how this relevant knowledge is used to timely provide required services and assistance.

In the context of health smart homes where a person is monitored, it is required to ensure a credible dependency evaluation of the subject with a high accuracy for detecting abnormal situations that may represent a risk for the human. Our application of the Grey model GM (1, 1) allows to predict the evolution of the health conditions based on the daily behavior and the energy consumption. Hence, the proposed system is constantly aware about the health status of the person and its dependency level using minimum data acquired with optimal sensing frequencies. Note that the energy consumption is used mainly because we believe that it reflects well the activities of the person in the home environment.

The experimentations performed with the Grey model, use the different x values presented in the adaptive monitoring applied with different scenarios using the same person's profile (Table 6.3) and with profile changes (Figure 6.4). We compare the traditional continuous monitoring and our proposed adaptive system with the forecasting model. The comparison comprises the resources consumption (computing, network, and energy), the detection of abnormal situations, and the dependency level evaluation.

Our prediction model, based on GM (1, 1), optimizes the monitoring system by learning first the normal daily behavior. Then, it extracts the real deviation of the elderly's behavior compared to the norm. Consequently, predictions are more accurate in understanding the person's context and in detecting the abnormalities of the daily behavior.

The abnormal detection with the forecasting model requires a higher frequency of monitoring and computing that are related to an extra number of activities. These activities are widely related to the nature of the possible abnormal situations. We can observe this difference by comparing the resources consumption between the adaptive monitoring (Table 6.2) and the predictive monitoring (Table 6.3) using the different X_3 and X_4 frequencies.

Figure 6.3 focuses on the comparison between our adaptive and predictive approaches using different profiles and the sensing frequencies X_3 and X_4. Note that the results regarding the adaptive and predictive monitoring are almost the same for the sensing frequencies X_1 and X_2 since there is a high frequency in sensing data that allows to monitor all the activities.

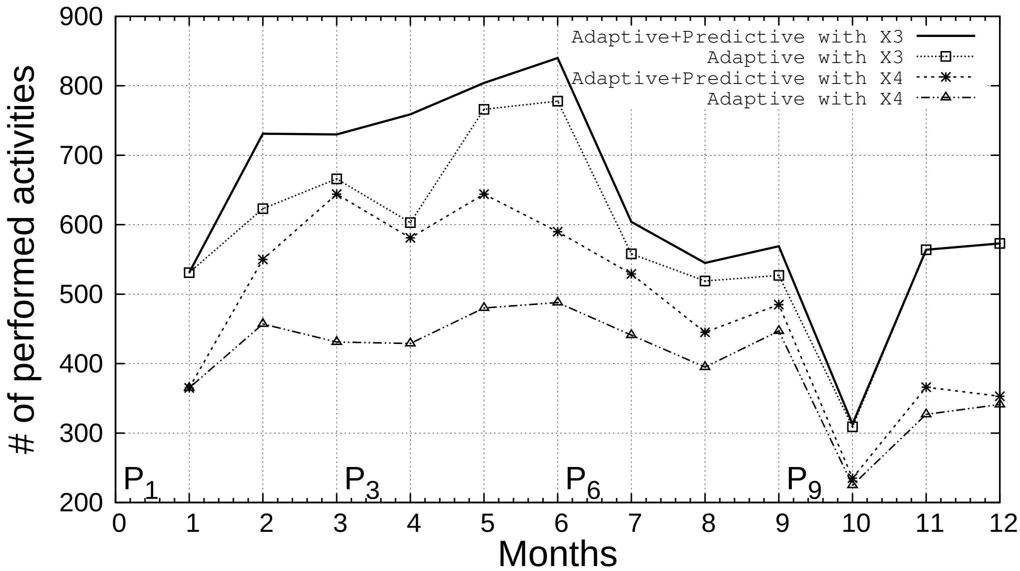

Figure 6.3 – Comparison between the *adaptive monitoring* (without prediction) and the *adaptive monitoring with prediction* in terms of number of monitored activities

Figure 6.4 shows the evaluation of the predictive monitoring with different profiles and using different sensing frequencies. In this figure, the comparison is performed between the *continuous* monitoring and the *adaptive monitoring with prediction* in terms of resources consumption. Specifically, the considered resources are the number of activities that are processed by the system (i.e. computation) presented in Figure 6.4-A, the energy consumption presented in Figure 6.4-B, and the network traffic presented in Figure 6.4-C. As explained, the prediction is achieved using the GM (1, 1)-based approach and considers the profile changes of the person from P_1 to P_9. The results are similar to those obtained with the adaptive approach. Consequently, even with a decline in the health status, ensuring a timely and context-aware monitoring does not imply a huge amount of data sensing if the monitoring algorithm is efficiently designed. In Figure 6.4-A, we observe that the system compute 61.5% of the daily activities with X_1, 54.3% with X_2, 38.3% with X_3, and 29.3% with X_4 compared to the continuous monitoring. Hence, an important amount of energy and network bandwidth is saved thanks to the consideration of only relevant data (Figure 6.4-B and 6.4-C).

We recall that an abnormal situation is tied to the unusual behavior in performing the daily activities in terms of durations, repeatability, and the person's absence activities. Based on our predictive model, the maximum and minimum

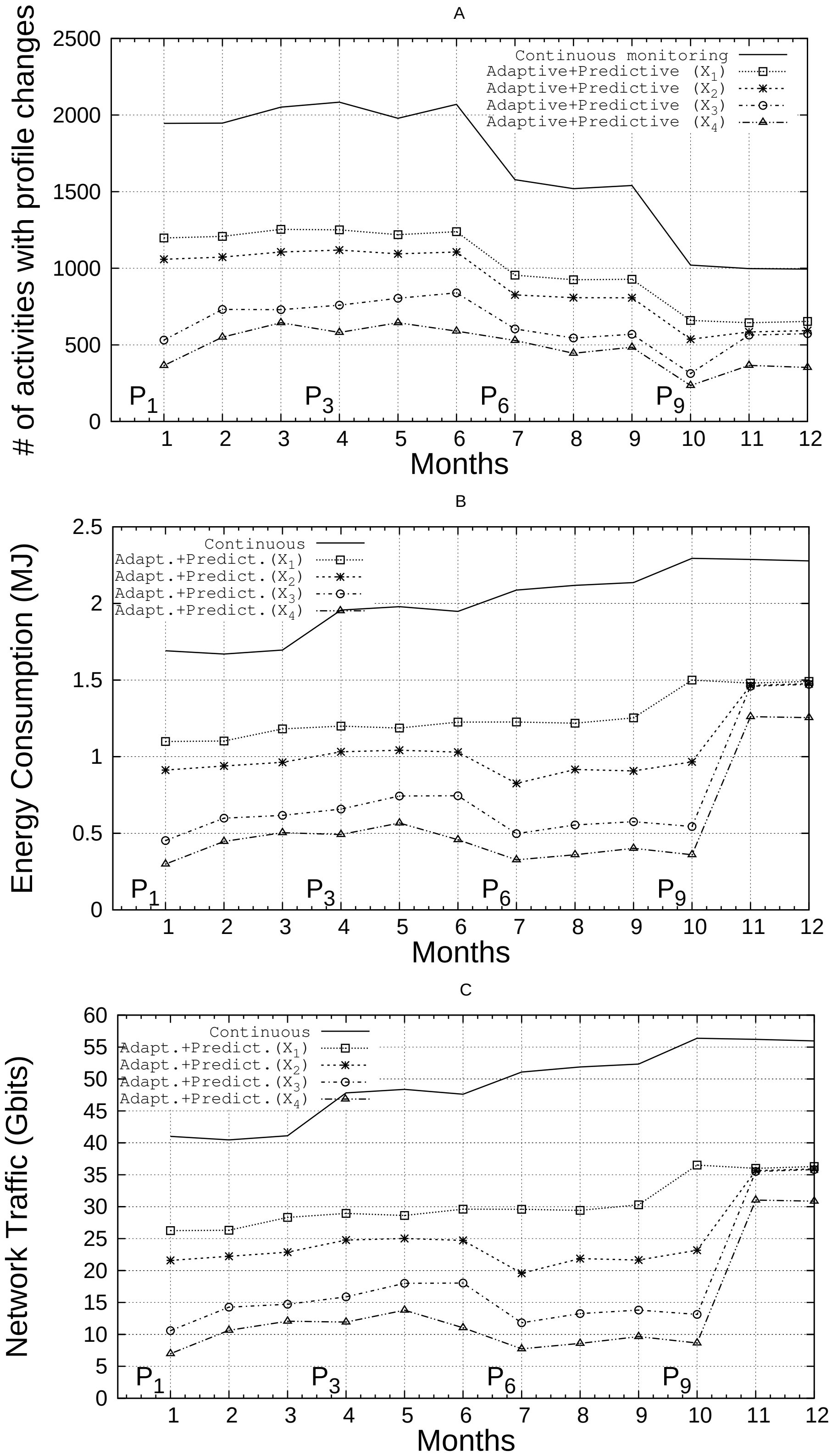

Figure 6.4 – Adaptive monitoring with GM (1,1)-based prediction and profile changes: (A) number of monitored activities, (B) energy consumption, and (C) network bandwidth consumption

values of durations and frequencies for each activity are computed as described in Section 6.3. Compared to prior periods, major differences that may occur in the achievement of a given activity, represent a notable change in the person's behavior. In other words, if performing the daily activities exceeds the expected values (forecasting range), the system will identify an abnormal behavior and thus updates the sensing frequency. Sensors are thus forced to continue the monitoring till the behavior becomes as usual. Table 6.4 gives an example current values and their forecasted values regarding some activities. The abnormal situations occur in the input scenario with some particular values regarding the performed activities and their nature.

Table 6.4 – Current and forecasting values of activities (duration/number) using the predictive model

Activity	**Forecasting values: duration(s) or number**			**Current values: duration(s)/number**		**Status**
	Grey value	**Min**	**Max**	**Duration** s	**Number**	
Meal preparation	2683	2146	3219	2450	-	regular
Meal preparation	6	4	8	-	6	regular
Take shower (washing)	843	543	1143	1199	-	irregular
Toileting	447	358	537	421	-	regular
Toileting	5	4	6	-	8	irregular
Sleep	28127	22501	33752	28366	-	regular
Medication use	1	1	1	-	0	irregular

Figure 6.5 compares the accuracy of the abnormal situations detection using different sensing frequencies. The X_1 frequency reflects the highest monitoring and provides a full detection of abnormal situations (a total of 529 cases). The results reveal that our proposed system, enriched with the predictive model of the person's behavior, succeed to ensure a high accuracy of detection with the same sensing frequency. Despite that X_2 senses 54.3% of the whole activities, the frequency matches the performance of X_1 and succeed to reach a prefect (100%) detection of abnormal situations. This result is due to the frequencies used in sensing, which are more context-aware. Indeed, the sensing depends on the nature of each activity and the probability that an abnormal situation could occur. For instance, the monitoring of some activities such as *Meal preparation* and *Washing* is always frequent and almost continuous if compared to other activities such as *Watching TV* and *Reading* that are monitored periodically and at low frequency. In the same Figure 6.5, we observe that the accuracy of the abnormal behavior detection is 95.8% with X_3 and 91.9% with X_4 using a sensing of 38.3 % and 29.3 % of the whole activities respectively.

Our deep study and experimentations of the human behaviour in smart spaces led us to the following observation. Generally, based on the daily behaviors for elderly, the subject who becomes more dependent tends predominantly to perform a fewer number (and hence fewer durations) of *ADL/IADL* activities (i.e. fewer frequencies) and, at the same time, spend a long time (duration) for *leisure* activities

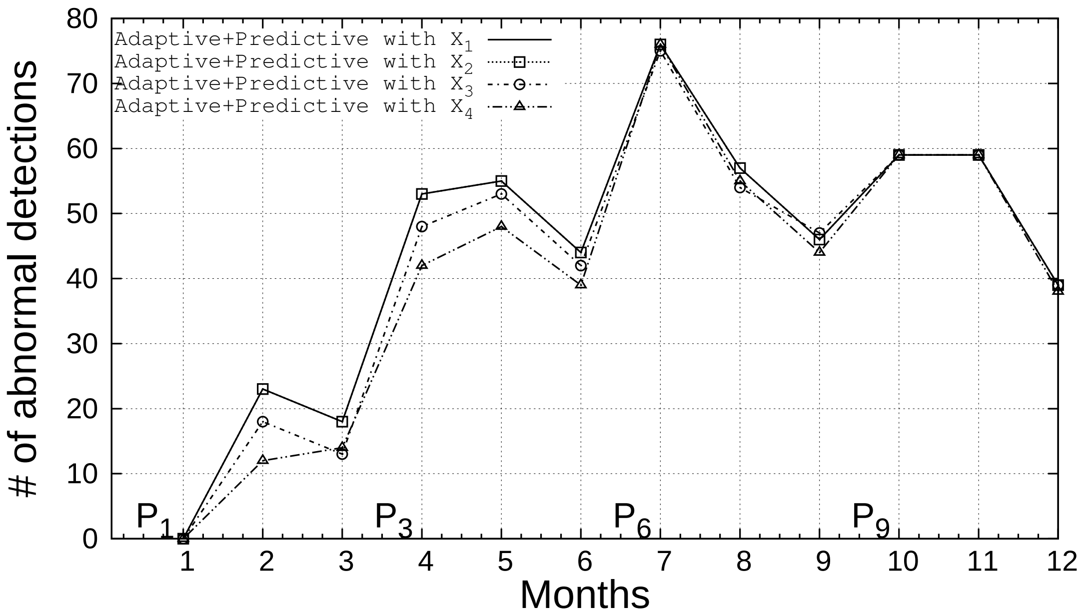

Figure 6.5 – Accuracy detection of abnormalities using an adaptive monitoring with the GM (1,1)-based prediction

with less mobility. In Figure 6.6-A, an example of the decrease in the number of basic activities when the dependency level increases. This example involves the number of *Meal preparation* activities, as a representative of the ADL class, which are performed by a person who lost his autonomy (i.e. declining profiles) during one year. In Figure 6.6-B, an example of duration increase regarding the leisure activities when the dependency level increases. The shown example (Figure 6.6-B) shows the durations spent in the *Watching TV* activity, as one leisure activity, of the same person and during the same period as in 6.6-A.

It is obvious that there is a strong relationship between the durations required in performing most of the activities in a given space and the person's consumption of energy in the same space. Indeed, the major part of the activities at home requires energy to be performed correctly, hence if a given activity takes a long time, the consumed energy will be high. Figure 6.7-A and 6.7-B show the durations required to achieve the ADL activities and leisure activities respectively during one year. The Figure 6.7-A. shows the observed and predicted durations required in performing the basic activities when the dependency level increases. The trend is a duration decrease regarding all the ADL activities. Figure 6.7-B shows the observed and predicted durations required in performing the leisure activities when the dependency level increases, the trend is increasing.

Based on these observations, it becomes interesting to use the person's own consumption of energy (used in performing ADL and leisure activities) as a good indicator to understand the person's behavior and predict future behavioral changes. For this, we classify the consumed energy required in performing the activities into two main categories. The first category is related to ADL and IADL activities. It represents the major part of activities such as *Meal preparation*, *Eating*, and *Washing*. The second category is related to *Leisure* activities and represents a

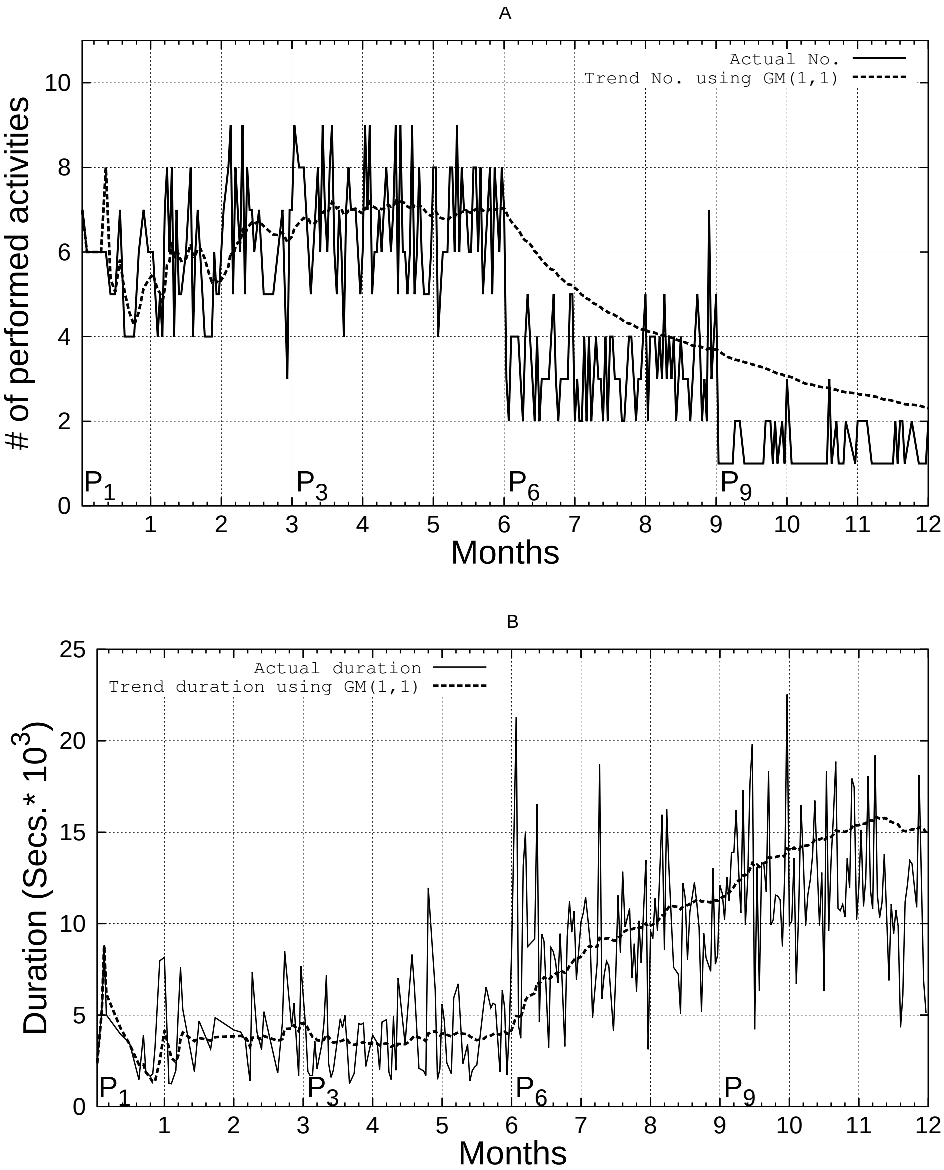

Figure 6.6 – Observed and predicted trends of the daily activities depending on the decline of the health status during one year: number of activities in meal preparation (A), duration of Watching TV (B)

minor part when compared to the previous category. It covers the energy required for activities like *Watching TV* and *Reading*.

The energy required to monitor the different activities is presented in Figure 6.8-A. The figure details the consumption for each category of activities (ADL/IADL and leisure) during one year. We compare the real and predicted values obtained by applying our GM(1,1)-based approach. In our system, the energy consumption is used as an indicator for detecting abnormalities as follows. An abnormal behavior is detected when the two following conditions are satisfied together (i.e. using a logic AND between the conditions). First, when the consumption of energy is less than the predicted values for important activities (i.e. ADL/IADL). Secondly, when the

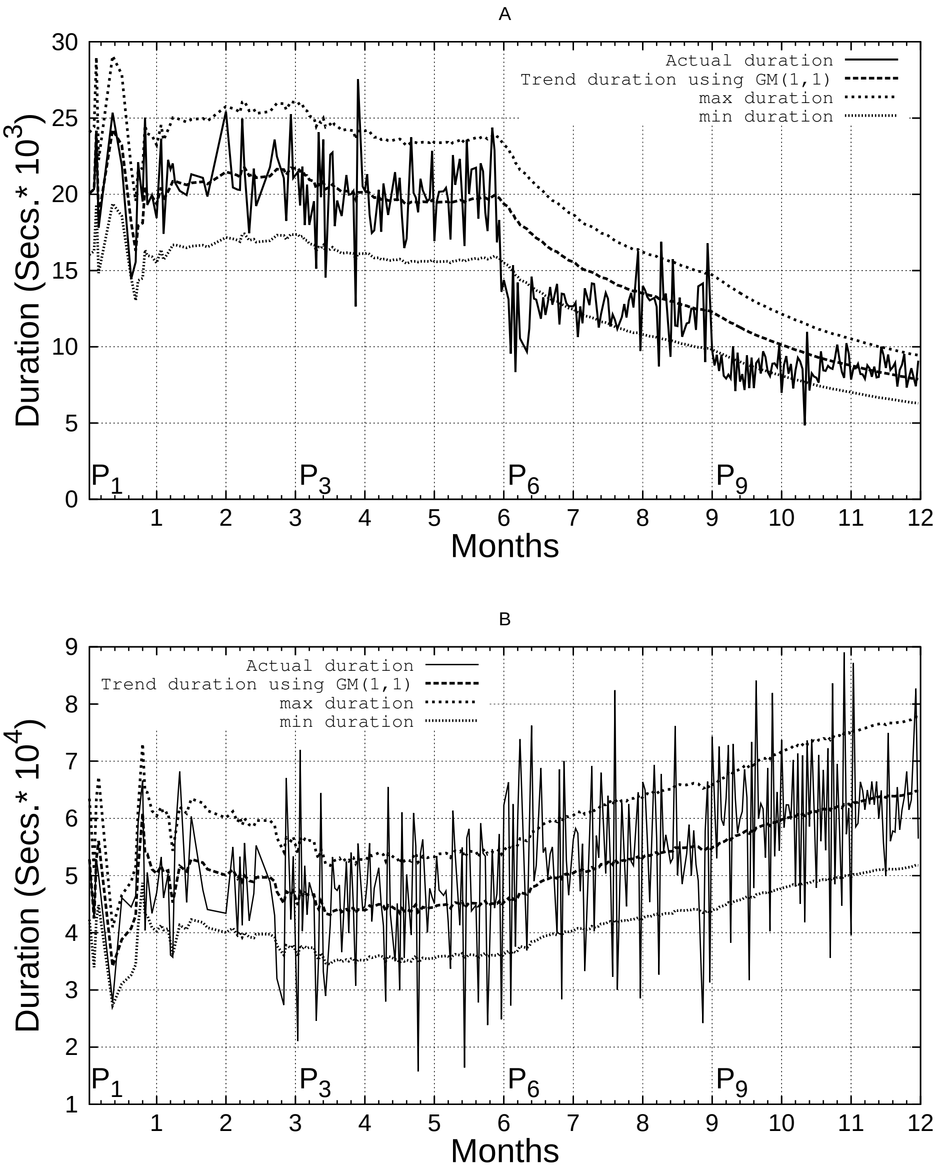

Figure 6.7 – Observed and predicted durations required in performing: ADL activities (A) and leisure activities (B)

used energy is more than the predicted values for leisure activities. The evaluation reveals that there were 20 changes detected by our system during the month number 7. Thus, there is a high probability that a significant change occurred regarding the person's profile. We observe also 16 detected changes during the month number 10 and a part of the monitoring does not indicate any changes (e.g. the last month). This is explained by the fact that the expected energy for leisure activities is higher than the real consumption, which makes our second condition, discussed previously, unsatisfied.

Figures 6.8-B and 6.8C. focus on (zoom in) the fourth and seventh months respectively. As we can observe during all of the fourth month (30 days), the system detects only two cases of abnormal behavior. Consequently, there is a low probability that these changes will affect the usual behavior of the person. However, during the seventh month, 20 cases of abnormalities were detected which means that there is a high probability that the person will change his usual behavior. If we check the input scenario of Figure 6.8-A, we can see that our energy-based reasoning complies with the real input scenario hence this reasoning can be used to predict future changes. Indeed, according to the input scenario, the person's profile changes from P_3 (month 6) to P_6 (month 7) which presents a loss of autonomy. Note that from the third to the fourth month, the person's profile changes from P_1 to P_3 but without a loss of autonomy since P_1, P_2, and P_3 represent the first category of autonomous persons (see Chapter 4).

6.6 Conclusion

In this Chapter, a predictive and efficient e-health monitoring of daily living activities in a smart environment has been proposed. The system is able to collect relevant and contextual data, detect abnormal behaviors and evaluate the person's dependency while remaining cost-efficient. Compared to a full continuous monitoring system, our proposed monitoring approach optimizes the resources (in terms of computing, network, and energy) and provides optimal sensing frequencies for high relevant data that are tied to the person's context. For instance, in the adaptive monitoring with different profiles of persons, the identified X_2 frequency of sensing gained 48.3% for the energy consumption, 49.3% for the network traffic, and required only a processing of 54.3% of the daily activities. The proposed forecasting model was able to predict the person's behavior by analyzing a minimum amount of sensed data with a short period of training. The proposed predictive approach has allowed to ensure a high accuracy in the detection of abnormal behaviors and unusual situations for all the dependency levels of monitored persons. Specifically, 100% of accuracy using a high monitoring (i.e. with the X_2 frequency), 95.8% using a medium monitoring (i.e. with X_3), and 91.9% with a minimum of monitoring (i.e. with the X_4 frequency).

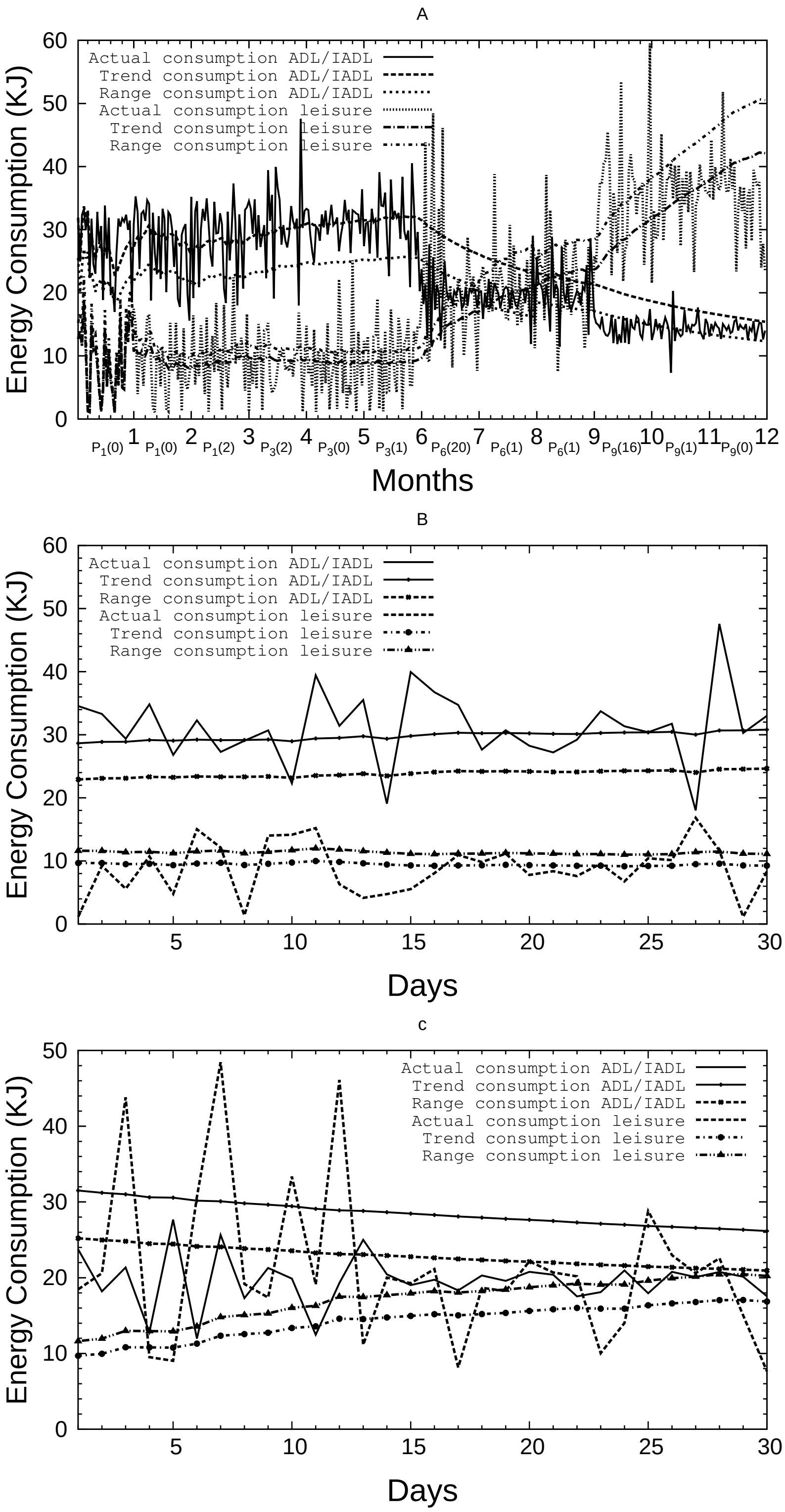

Figure 6.8 – The use of the power consumption as indicator to understand the person's behavior and predict the profile changes: predictive values for the whole year (A), zoom in the fourth month (B), zoom in the seventh Month (C)

CHAPTER 7

Conclusion and Perspectives

Contents

7.1 Conclusion

To face the growing demand for e-health monitoring services for elderly and dependent persons, the design of an efficient adaptive and context-aware system becomes necessary. Such systems monitor the person's behavior and activities of daily living and timely provide required help and assistance particularly when risky and abnormal situations occur.

The aim of this research was to investigate the e-health monitoring systems in a smart environment and develop efficient approaches that provide revelvant services while keeping a strong link with the existing medical knowledge. We have investigated such knowledge and how it can be adopted in HSH for a best support of the independent living of persons. We have proposed an adaptive and predictive context-aware monitoring system. The research was conducted to enhance the efforts for providing better understanding of the elderly's context regarding the activities of daily living, detection of behavioral patterns, and prediction of future health conditions. Different approaches and monitoring algorithms using several statistical analysis and mathematical prediction have been proposed in this thesis. Many experimentations were applied on simulated dataset scenarios generated using statistical methods. The evaluations of the system have been conducted for experimenting the validity of the proposed monitoring algorithms in terms of adaptability, efficiency of the sensing frequencies selection, and the performance and accuracy of the prediction regarding the evolution of the person's conditions.

In order to orient the reader, recall that the concept of person's context considered through the manuscript does not consider the ambient context of the user as a whole, but the "context of user's autonomy" (i.e. level of dependency) as evaluated using the most current geriatrics scales. Moreover, the optimization of the health monitoring is only limited to the management of the technical resources which are mainly bandwidth, and energy consumption. Regarding the reduction of intrusiveness of the user's life, it is only suggested through the reduction of the number of information transferred and exchanged with the outside. Furthermore, all experimentation results presented in this work were restricted to simulated datasets and scenarios that we tried to make them as realistic as possible based on the evolution de daily activities during long periods.

The main conclusions regarding the different aspects of the thesis are presented below.

We presented a comprehensive survey study of the context-aware computing in the healthcare field for elderly. The objective was to highlight the requirements, technologies, and the main challenges facing the development of health monitoring in smart environments. We identified a set of guidelines that would help interested readers and researchers to understand the issues that need to be addressed in order to provide context-aware services and improve them for the elderly and patients. We identified and discussed the main important components required in HMS (sensing, communications, and processing) in details. Moreover, we presented a consolidated picture of the most important functions and services offered by HMS for monitoring and detecting the human's behavior including concepts, approaches, and processing methods. We provided a survey of the recent research and evaluate the state of the art of healthcare applications and monitoring systems and discussed some research challenges for future healthcare applications[**?**].

In this deep survey study, we identified the main weaknesses in existing healthcare systems such as the lack of true understanding of the person's context regarding the achievement of basic activities of daily living and health status. We show how the systems operate in isolation from the real requirements of the healthcare institutions and the negative impact of the absence of a link between monitored data and health status evaluation and inference (e.g. the dependency level). We observed that none of the existing approaches systematically consider the elderly' context (health and behavior) as it is defined in the geriatric domain. Indeed, health and behavioral systems for elderly are defined based on the availability of sensing rather than the use of medical knowledge and a good understanding of the elderly context. We believe that without such knowledge and understanding, any efforts in improvinging the quality of healthcare services for elderly using smart home technologies would be ad-hoc and cannot be expected to provide desired results. Moreover, the traditional health monitoring approaches and context-aware assisted living systems tended to manage all the sensed data with unconditional processing. Most of these approaches adopt a continuous monitoring that maintains the transfer data channels available all the time whatever the person's context. Several related problematic were presented previously at the outset of this thesis. In the literature, several methods were applied for detecting the human's behavior and extract the context in health smart environments. These approaches typically require substantial amounts of training data to learn and detect the behavior and context. Therefore, such methods can provide a good performance but with a high computational cost. We concluded that there are still a need to improve the intelligent processing in health monitoring systems which would combine an optimal monitoring cost with an accurate detection and prediction of the person's behavior.

In HMS, the medical knowledge and expertise should be applied in order to ensure and validate that the behavior pattern changes correlate to the health status change of the monitored person. Moreover, it is desirable to provide a better understanding of the context of persons in order to provide e-health services that meet the person's context and real needs. The consideration of such knowledge helps to improve context-aware e-health systems and make easier the integration of the new proposed e-health systems into health institutions. Moreover, the context-aware monitoring applications developed to detect the human behavior need a clear description of the nature of human activities and their characteristics. In this thesis, we described the person context regarding the achievement of activities of daily living and consider the dependency evaluation models used in geriatrics. We provided a better understanding of the targeted activities that should be considered in HSH scenarios. We described a taxonomy of activities and their characterization in a manner that is meaningful for elderly and dependent persons monitoring systems.

In this thesis, we improved the knowledge about the context of the monitored person which is the set of activities of daily living that should be monitored, and show how they affect the performances of health monitoring systems. The monitored person's context has been considered by studying and comparing the existing health models used in the evaluation of dependent people. The focus was on accurately meeting the needs of dependent people for appropriate healthcare services. We addressed the most famous models used in geriatrics field to evaluate the dependency degree of persons. The AGGIR model, used in France, and the SMAF model, used in Canada were considered. The compatibility between the two models was discussed including the model considered activities (items), results, and classification. Some light was shed on the weakness of the dependency models used in the health domain which help to improve the consideration of the person's context and focus on the main activities to be monitored.

According to the discussed experimentations and proposed matching algorithm, our research has clearly shown that neither the SMAF nor the AGGIR models can fulfill the requirements of ensuring the efficiency and reliability of e-health platforms services. The presented simulations have handled a huge amount of data (twenty trillion ($5^{19}.4^{10}$) of possible situations (evaluations). Each processed situation represented a person with a certain degree of dependency. The simulations results led us to realize that the existing models are inadequate and not efficient to give an accurate assessment about the elderly dependency. Indeed, the existing models do not reflect the real context of the person and, as we have shown, the same subject can be considered as autonomous by using one model and seen to be a dependent person in another model. Consequently, in order to further reduce the error rate in existing models and build efficient e-health ecosystems, we should improve the performance of the evaluation methods. Our investigation revealed that the SMAF model provides a better knowledge than the AGGIR model regarding the context of persons and the evaluation of patients' needs in terms of help and assistance. This fact is due to the model's coverage of the most important daily activities and the used classification of persons into profiles according to the specific needed services.

Like other geriatric models, the SMAF model has shown some weaknesses in different aspects and the model needs a clear improvement in order to be adopted in new e-health platforms which accommodate both efficiency and reliability. Existing models lacks validity periods regarding the evaluation of activities. Indeed, the model's evaluation remains unchanged after the latest achieved evaluation. Moreover, in some situations, the existing models exaggerate their evaluation (hence, the required frequency to evaluate/sense the activities) by considering some unuseful activities in situations of severe dependency. In the ecosystem of e-health services, linking the concept of validity periods to each monitored activity is of high importance while providing context-aware services. Indeed, in order to ensure efficient services in time, the validity of sensed data should be dependent on the type of the activity and the necessity of updates with a well-determined threshold. For optimizing e-health platforms, some activities have not to be monitored or measured all the time. For instance, in severe dependency levels, it is not necessary to monitor the grooming activity all time by models and platforms. This improves the architecture to sense some activities, which directly affect the lives of the persons while maintaining the same quality of the monitoring. Consequently, we have to monitor only appropriate activities that could trigger some services.

In this thesis, we proposed an adaptive and predictive context-aware monitoring system that tackles the drawback and weakness of existing e-health solutions. Our aim was to improve the effectiveness of the e-health monitoring while maintaining a strong link with existing medical methods and knowledge, such as the models used in the geriatric domain, and providing an optimal use of the resources such as energy, network, and computation. Based on the considered health knowledge provided, we succeed to determine: *what*, *when* and *how* to monitor, gather and analyze data related to the person's context. Sensing and analyzing daily activities are tied to the *type* of the monitored activity, its *complexity*, *repeatability*, and the *duration* required to achieve it.

The developed adaptive context-aware framework for e-health monitoring system for smart environments is capable to dynamically adapt the monitoring mode depending on: the person's context, his history, and the nature of monitored activities. The framework is based on the knowledge of the person's behavior and the usual energy consumption for each activity. The system requires only short training periods and a minimum amount of sensed data using a statistical analysis and mathematical prediction. Unlike existing solutions and traditional e-health monitoring systems, our proposed approaches used a smart conditional processing scheme to optimize the system resources and adapt their use to the current context of the monitored person. Particularly, the person's profile which includes the dependency level and historical records represent the essential key in motivating the sensor nodes for an optimal sensing frequency in order to process only high relevant data. Consequently, the proposed approach solved the main issues associated with traditional monitoring schemes and only deals with the necessary collected data. Our framework was able to learn the human behavior, automatically evaluate the person's dependency, anticipate the deteriorations of the health status before a possible major complication, and predict the future health condition. The framework optimized the use of resources (network, energy, and processing) without compromising the quality of the monitoring service and maintaining the system's ability to detect abnormal situations.

In our propositions, we modeled the daily life behavior and generate rich dataset series. We defined a new scenario generation strategy based on the Markovian model to consider different person profiles and situations. The objective was to generate a rich and realistic sequence of activities of a person with or without disabilities and for a long period. The definition of a pseudo variable-length Markovian model has allowed the generation of long-term realistic scenarios that can be used for real-life implementations and testing with a high flexibility and without a risk for a real person. Our dataset described the performances of the elderly regarding the achievements of the daily life activities. The different scenarios included in the dataset involved sequences of activities which were achieved, during a whole year, by an elderly with different levels of dependency. The generation of simulated ADL scenarios (datasets) provided sufficient data to help the design and the test of approaches defined for health smart spaces and assisted living systems. The representation of the experimental dataset involved different formats, codes, and names for actions and for high-level activities composed of atomic actions. An overview of the activity can be simply presented using time series using the format: [day's number, starting time, day's number, ending time, activity name].

Another contribution of our thesis was the development of a forecasting technique using the Grey Model theory GM (1, 1) to detect the human's behavior changes with the ability to predict the evolution of the health conditions. The proposed model ensured a prediction of the health condition of persons based on the observed behavior in performing the daily activities and using the knowledge related to the energy consumption that reflects well the activities of the person. GM (1, 1)-based predictions used the increasing or decreasing trend in achieving several activities of daily living which, in turn, was used to predict the future health conditions. Unlike other health monitoring systems and prediction approaches which typically require substantial amounts of training data, our proposed system provided a proactive attention, by only using high relevant data, and is able to trigger notifications to caregivers if a high probability of decline is detected.

Contrary to the majority of traditional health monitoring systems that tend to monitor and interpret all data, the proposed approaches in this thesis succeeded to ensure a high accuracy regarding the evaluation of the person's dependency and behavioral patterns learning. the approaches included the prediction of future health condition and provided high accuracy for detecting the abnormal and unusual situations for all the levels of the person's dependency, as well as to ensure efficient sensing frequencies and combine a good optimization of the resources.

The optimization of resources concerned many dimensions like computing (i.e. the collection of relevant and contextual data), network traffic, and energy consumption. For instance, in the adaptive monitoring with different profiles of persons, the identified X_2 frequency of sensing gained 48.3% for energy consumption, 49.3% for network traffic and required a processing of only 54.3% of the daily activities. With sensing a very low amount of data, our proposed system succeeded to gain a perfect accuracy (100%) for the evaluation of the person dependency level (hence, in the decline detection). The proposed forecasting model was able to predict the person's behavior by analyzing a minimum amount of sensed data with a short period of training. The proposed predictive approach has allowed to ensure a high accuracy in the detection of abnormal behaviors and unusual situations for all the dependency levels of monitored persons with a 100% of accuracy in high monitoring (with the X_2 frequency), and 95.8% in the medium monitoring (with the X_3 frequency) and 91.9% with a minimum of monitoring (i.e. with X_4).

7.2 Perspectives

Based on the achieved work of this thesis, we identified the following future research and further investigations:

- The experimentation results and analyses presented in this work were restricted to simulated datasets and scenarios. Even though the datasets were realistic and cover a long period, the experimental tests with real-world data, under real conditions and with complex infrastructures need to be investigated.

- Further investigation is required to implement the approaches presented in this thesis for multiple users with different behaviors and who evovle concurrently in a smart environment. The identification of persons can be guaranteed using any kind of techniques such as RFID. A prospective study is to investigate the adaptability of the proposed system with multiple occupants and show how the system can be affected by the presence of additional visitors. This represents a complex task. Indeed, in such situations, the monitoring will be not dedicated for a single or multiple known users. Moreover, the system has to handle and consider the visitor's number, visiting time, and how can this change the evaluation of the residents' health and their behavioral context.

- This study can serve as a base for future studies concerning the generation of dataset scenarios as a tool to describe the performances of the elderly regarding the achievements of the daily life activities from the geriatrics domain point of view. More improvements are needed to the current dataset by considering the temporal logic between activities (time interval) including sequential, concurrent, and interleaved activities. In addition, several parameters should be added for more realistic scenarios such as seasons, locations, gender, age, etc.

- More investigation is needed to evaluate some critical activities and mental functions such as activities related to judgment, hearing, and speaking as defined in the SMAF model. Some methods such as TV questionnaires' achieved automatically in smart environment by elderly represent an interesting mean.

- It would be interesting to develop and integrate software systems that accommodate most of the health evaluation models as defined by the geriatrics domain and based on our proposed approaches with various activities and evaluation mechanisms inside the health institutions systems. Such software can be used to test the performance proposals and monitoring algorithms in health smart spaces.

- It is interesting to extend our work to develop more contextual system by investigating the relation between basic activity of daily living and physiological activities. For future planning, we can link and extend the monitoring system by the consideration of vital signs and the consideration of new constrained environments mainly within the Body Area Networks (BAN).

- The forecasting technique used in this thesis could be extended to predict more complex human behaviour. In addition, one can consider the combination and the test of several prediction models and the evaluation of their impact in term of anticipating risky situations and use of resources.

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Publications

The following publications have been published as a direct result of this thesis work.

Refereed Journal Papers

- Haider Mshali, Tayeb Lemlouma, and Damien Magoni. Adaptive Monitoring System for e-Health Smart Homes. Submitted to the *Journal of Pervasive and Mobile Computing* (Elsevier) in 2016.
- Haider Mshali, Tayeb Lemlouma, and Damien Magoni. A Survey on Health Monitoring Systems for Smart Health Homes. Submitted to the *International Journal of Industrial Ergonomics* (Elsevier) in 2016.

Refereed Conference Papers

- Haider Mshali, Tayeb Lemlouma, and Damien Magoni. Analysis of dependency evaluation models for e-health services. In the proceedings of the 58th IEEE Global Communications Conference (IEEE GlobeCom), Austin, USA, pages 2429-2435, 2014.
- Haider Mshali, Tayeb Lemlouma, and Damien Magoni. Context-aware adaptive framework for e-health monitoring. In the proceedings of the 11th IEEE International Conference on Green Computing and Communications (IEEE GreenCom), merged with IEEE DSDIS, Sydney, Australia, pages 276-283, 2015.
- Haider Mshali, Tayeb Lemlouma, and Damien Magoni. A predictive approach for efficient e-health monitoring. In the proceedings of the 17th IEEE International Conference on e-Health Networking, Applications and Services (IEEE HealthCom) Boston, USA, pages 268-273, 2015.

Appendices

APPENDIX A

Katz Index of Independence in Activities of Daily Living

Patient Name:_____________________ **Date:**____________

Patient ID #_______________________

Katz Index of Independence in Activities of Daily Living		
Activities Points (1 or 0)	**Independence** (1 Point) **NO** supervision, direction or personal assistance.	**Dependence** (0 Points) **WITH** supervision, direction, personal assistance or total care.
BATHING Points: __________	**(1 POINT)** Bathes self completely or needs help in bathing only a single part of the body such as the back, genital area or disabled extremity.	**(0 POINTS)** Need help with bathing more than one part of the body, getting in or out of the tub or shower. Requires total bathing
DRESSING Points: __________	**(1 POINT)** Get clothes from closets and drawers and puts on clothes and outer garments complete with fasteners. May have help tying shoes.	**(0 POINTS)** Needs help with dressing self or needs to be completely dressed.
TOILETING Points: __________	**(1 POINT)** Goes to toilet, gets on and off, arranges clothes, cleans genital area without help.	**(0 POINTS)** Needs help transferring to the toilet, cleaning self or uses bedpan or commode.
TRANSFERRING Points: __________	**(1 POINT)** Moves in and out of bed or chair unassisted. Mechanical transfer aids are acceptable	**(0 POINTS)** Needs help in moving from bed to chair or requires a complete transfer.
CONTINENCE Points: __________	**(1 POINT)** Exercises complete self control over urination and defecation.	**(0 POINTS)** Is partially or totally incontinent of bowel or bladder
FEEDING Points: __________	**(1 POINT)** Gets food from plate into mouth without help. Preparation of food may be done by another person.	**(0 POINTS)** Needs partial or total help with feeding or requires parenteral feeding.
TOTAL POINTS: ________	**SCORING:** 6 = High (*patient independent*) 0 = Low (*patient very dependent*	

Source:
try this: Best Practices in Nursing Care to Older Adults, The Hartford Institute for Geriatric Nursing, New York University, College of Nursing, www.hartfordign.org.

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APPENDIX B

The Lawton Instrumental Activities of Daily Living Scale

Patient Name:______________________ **Date:**_____________

Patient ID #_________________________

LAWTON - BRODY
INSTRUMENTAL ACTIVITIES OF DAILY LIVING SCALE (I.A.D.L.)

Scoring: For each category, circle the item description that most closely resembles the client's highest functional level (either 0 or 1).

A. Ability to Use Telephone		**E. Laundry**	
1. Operates telephone on own initiative-looks up and dials numbers, etc.	1	1. Does personal laundry completely	1
2. Dials a few well-known numbers	1	2. Launders small items-rinses stockings, etc.	1
3. Answers telephone but does not dial	1	3. All laundry must be done by others	0
4. Does not use telephone at all	0		
B. Shopping		**F. Mode of Transportation**	
1. Takes care of all shopping needs independently	1	1. Travels independently on public transportation or drives own car	1
2. Shops independently for small purchases	0	2. Arranges own travel via taxi, but does not otherwise use public transportation	1
3. Needs to be accompanied on any shopping trip	0	3. Travels on public transportation when accompanied by another	1
4. Completely unable to shop	0	4. Travel limited to taxi or automobile with assistance of another	0
		5. Does not travel at all	0
C. Food Preparation		**G. Responsibility for Own Medications**	
1. Plans, prepares and serves adequate meals independently	1	1. Is responsible for taking medication in correct dosages at correct time	1
2. Prepares adequate meals if supplied with ingredients	0	2. Takes responsibility if medication is prepared in advance in separate dosage	0
3. Heats, serves and prepares meals, or prepares meals, or prepares meals but does not maintain adequate diet	0	3. Is not capable of dispensing own medication	0
4. Needs to have meals prepared and served	0		
D. Housekeeping		**H. Ability to Handle Finances**	
1. Maintains house alone or with occasional assistance (e.g. "heavy work domestic help")	1	1. Manages financial matters independently (budgets, writes checks, pays rent, bills, goes to bank), collects and keeps track of income	1
2. Performs light daily tasks such as dish washing, bed making	1	2. Manages day-to-day purchases, but needs help with banking, major purchases, etc.	1
3. Performs light daily tasks but cannot maintain acceptable level of cleanliness	1	3. Incapable of handling money	0
4. Needs help with all home maintenance tasks	1		
5. Does not participate in any housekeeping tasks	0		
Score		**Score**	

Total score__________________

A summary score ranges from 0 (low function, dependent) to 8 (high function, independent) for women and 0 through 5 for men to avoid potential gender bias.

Source: *try this:* Best Practices in Nursing Care to Older Adults, The Hartford Institute for Geriatric Nursing, New York University, College of Nursing, www.hartfordign.org.

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APPENDIX C

Barthel Index of Activities of Daily Living

THE BARTHEL INDEX	**Patient Name**:	____________________
	Rater Name:	____________________
	Date:	____________________

Activity **Score**

FEEDING
0 = unable
5 = needs help cutting, spreading butter, etc., or requires modified diet
10 = independent ______

BATHING
0 = dependent
5 = independent (or in shower) ______

GROOMING
0 = needs to help with personal care
5 = independent face/hair/teeth/shaving (implements provided) ______

DRESSING
0 = dependent
5 = needs help but can do about half unaided
10 = independent (including buttons, zips, laces, etc.) ______

BOWELS
0 = incontinent (or needs to be given enemas)
5 = occasional accident
10 = continent ______

BLADDER
0 = incontinent, or catheterized and unable to manage alone
5 = occasional accident
10 = continent ______

TOILET USE
0 = dependent
5 = needs some help, but can do something alone
10 = independent (on and off, dressing, wiping) ______

TRANSFERS (BED TO CHAIR AND BACK)
0 = unable, no sitting balance
5 = major help (one or two people, physical), can sit
10 = minor help (verbal or physical)
15 = independent ______

MOBILITY (ON LEVEL SURFACES)
0 = immobile or < 50 yards
5 = wheelchair independent, including corners, > 50 yards
10 = walks with help of one person (verbal or physical) > 50 yards
15 = independent (but may use any aid; for example, stick) > 50 yards ______

STAIRS
0 = unable
5 = needs help (verbal, physical, carrying aid)
10 = independent ______

TOTAL (0–100): _____

APPENDIX D

Functional independence measure (modified by [281])

	Score (1–7)
Motor	
Self-care	
(A) Eating	□
(B) Grooming	□
(C) Bathing	□
(D) Dressing—upper body	□
(E) Dressing—lower body	□
(F) Toileting	□
Sphincter control	
(G) Bladder management	□
(H) Bowel management	□
Transfers	
(I) Bed<comma> chair<comma> wheelchair	□
(J) Toilet	□
(K) Tub<comma> shower	□
Locomotion	
(L) Walk/wheelchair	□
(M) Stairs	□
Cognitive	
Communications	
(N) Comprehension	□
(O) Expression	□
Social cognition	
(P) Social interaction	□
(Q) Problem solving	□
(R) Memory	□
Total FIM score	□

Note: Leave no blanks. Enter 1 if patient not testable due to risk.

Levels of dependence	**FIM™ score**
Independent	
Complete independence (timely, safely)	7
Modified independence (device)	6
Modified dependence	
Supervision (subject = 100%)	5
Minimal assist (subject = 75%)	4
Moderate assist (subject = 50%)	3
Complete dependence	
Maximal assist (subject ≥ 25%)	2
Total assist (subject = less than 25%)	1

APPENDIX E

APPENDIX – Northwick Park Dependency Score

Note: Copies of the NPDS and instruction manual can be obtained from Lynne Turner-Stokes, Regional Rehabilitation Unit, Northwick Park Hospital, Watford Road, Harrow, Middlesex HA1 3UJ, UK.

For each item, circle the highest score that applies
and answer any additional questions.

		Dependency score
1)	Mobility	
	Walks fully independently	0
	Independent in electric/self-propelled chair	1
	Walks with assistance/supervision of one	2
	Uses attendant-operated wheelchair	3
	Bed-bound (unable to sit in wheelchair)	4
2)	Bed transfers	
	Fully independent	0
	Requires help from one person	1
	Requires help from two people	2
	Requires hoisting by 1 person and takes <1/2 hour	3
	or Requires hoisting by two people and takes <1/4 hour	3
3)	Toileting	
	How many times do they need to pass urine during the day?	.....
	How many times do they need to pass urine during the night?	.....

3.1) Toileting: bladder

(Includes getting there, transferring on to toilet, cleaning themselves, adjusting clothing, and washing hands afterwards. If using bottle: includes reaching for it, positioning and replacing it unspilt.)

	Able to empty bladder independently	0
	Set-up only (e.g. copes if bottles left within reach) *or* Has in-dwelling catheter/convene	1
	Needs help from 1, and takes <1/4 hour	2
	Needs help from 1, and takes more than 1/4 hour	3
	Takes more than 1/2 hour *or* Needs help from 2	4
3.2)	Urinary incontinence	
	No accidents or leakage from catheter/convene	0
	Continent if toiletted regularly. Occasional accidents	1
	1–2 episodes of incontinence/leakage in 24 hours	2
	≥3 episodes of incontinence/leakage in 24 hours	3
	If scored 1: How often per week?	....
	If scored 3: How often per day?	....

7) Dressing

(Includes putting on shoes, socks, tying laces, putting on splint or prosthesis.)

Able to dress independently	0
Needs help to set up only (e.g. laying out clothes) *or* Needs incidental help from 1 (e.g. just with shoes)	1
Needs help from 1, and takes <$^1/_2$ hour	2
Needs help from 1, and takes more than $^1/_2$ hour	3
Needs help from 2, and takes <$^1/_2$ hour	4
Needs help from 2, and takes more than $^1/_2$ hour	5

8.1) Eating

Entirely gastrostomy/nasogastric fed – go to 8.3	0
Able to eat independently	0
Needs help to set up only (e.g. opening packs or passing special cutlery)	1
Needs help from 1, and takes <$^1/_2$ hour	2
Needs help from 1, and takes more than $^1/_2$ hour	3

8.2) Drinking

Entirely gastrostomy/nasogastric fed – go to 8.3	0
Able to pour own drink and drink it independently	0
Able to drink independently if left within reach	1
Needs help or supervision, and takes <$^1/_2$ hour	2
Needs help or supervision, and takes >$^1/_2$ hour	3

8.3) Enteral feeding (gastrostomy or nasogastric tube)

No enteral feeding	0
Able to manage feeds entirely independently	0
Needs help to set up feed just once a day/night	1
Needs help to set up feed twice a day	2
Needs help to set up feed three times a day	3
Needs help to set up feeds or give extra flushes during the night	4

9) Skin pressure relief

Skin intact and able to relieve pressure independently	0
Needs prompting only to relieve pressure	1
Skin intact, needs help from 1 to turn (4 hourly)	2
Skin intact, needs help from 2 to turn (4 hourly)	3
Skin marked or broken, needs 1 to turn (2 hourly)	4
Skin marked or broken, needs 2 to turn (2 hourly)	5

10) Safety awareness

Fully orientated, aware of personal safety	0
Requires some help with safety and orientation but Safe to be left for >2 hours and could summon help in emergency	1
Requires help to maintain safety Could not be left for ≥2 hours and could not summon help in an emergency	2
Requires constant supervision	3

4) Opening bowels (or emptying colostomy bag)

How many times do they open their bowels per day? ....
or per week? ....

4.1) Toileting: bowels

(Includes getting to and transferring on to toilet, cleaning themselves, adjusting clothing, and washing hands afterwards. If has colostomy, includes emptying/changing bag hygienically.)
NB: Do not include faecal incontinence here.

Able to empty their bowels independently	0
Set-up only (e.g. giving suppositories/enema)	1
Needs help/supervision from 1, and takes <1/4 hour	2
Needs help from 1, and takes more than 1/4 hour	3
Needs help from 2, and takes <1/4 hour	4
Needs help from 2, and takes more than 1/4 hour	5

4.2) Faecal incontinence

No faecal accidents	0
Requires regular bowel regimen in order to remain continent	1
Occasional faecal accidents (less than daily)	2
Regular incontinence of faeces	3

If has faecal accidents: How often per week? ....

5) Washing and grooming

(Includes washing hands and face, cleaning teeth, brushing hair, and shaving or make-up.)
NB: This item does not include bathing/showering.

Able to wash and groom independently	0
Needs help to set up only (e.g. laying out things, filling bowl with water)	1
Needs help from 1, and takes <$^1/_2$ hour	2
Needs help from 1, and takes more than $^1/_2$ hour	3
Needs help from 2, and takes <$^1/_2$ hour	4
Needs help from 2, and takes more than $^1/_2$ hour	5

Note: It is very rare to need help from 2 to wash unless patient requires restraint

6) Bathing/showering

(Includes getting to bath/shower-room, transferring in and out, washing and drying.)

NB: If unable to bath or shower, complete as for thorough stripwash.

Able to have bath/shower independently	0
Needs help to set up only (e.g. running bath, soaping flannel, etc.)	1
Needs help from 1, and takes <$^1/_2$ hour	2
Needs help from 1, and takes more than $^1/_2$ hour	3
Needs help from 2, and takes <$^1/_2$ hour	4
Needs help from 2, and takes more than $^1/_2$ hour	5

11)	**Communication**	
	Able to communicate all needs	0
	Able to communicate basic needs without help	1
	Able to communicate basic needs with a little help/using communication aid	2
	Able to respond to direct questions about basic needs	3
	Unable to understand questions, but responds to gestures/contextural cues	4
	No effective means of communication	5
12)	**Behaviour**	
	Compliant and socially appropriate	0
	Needs verbal/physical prompting for daily activities	1
	Needs persuasion to comply with rehabilitation or care	2
	Needs structured behavioural modification programme	3
	Disruptive, inclined to aggression	4
	Inclined to wander off ward/out of house	5
13)	**Total Basic Care Needs**	Total ....
14)	**Special Needs: add 5 for each of the below**	
	A) Tracheostomy	5
	B) Open pressure sore/wound requiring dressings	5
	C) >2 interventions required at night	5
	D) Patient or relatives need substantial psychological support	5
	E) Requires isolation (e.g. for MRSA (multiply resistant *Staphylococcus aureus)* screening/colonization)	5
	F) Intercurrent medical/surgical problem	5
	G) Needs one-to-one 'specialing'	5
15)	**Total Special Nursing Needs**	Total ....
16)	**Total dependency**	Total ....

Titre : Services e-Santé sensibles au contexte dans les espaces intelligents

Résumé : Dans cette thèse, nous proposons un nouveau système e-santé sensible au contexte pour les sujets âgés, dépendants et isolés. Le système surveille et suit les activités de la vie quotidienne (AVQ) de la personne tout en considérant les standards les plus utilisés en gériatrie pour l'évaluation du niveau de dépendance tel que le modèle SMAF. Le cadre de travail proposé offre automatiquement de nombreux services adaptables tels que la collection d'informations pertinentes et contextuelles et l'évaluation de l'état de santé en se basant sur le niveau de dépendance. Les approches proposées permettent d'apprendre le mode de vie des sujets en se basant sur l'accomplissement des AVQ et la détection des changements de comportement qui peuvent représenter un risque pour la personne. Pour se rapprocher de la vie réelle, nous avons généré des longs scénarios réalistes en définissant un modèle Markovien. Concernant la prédiction du comportement, nous proposons une nouvelle approche basée l'extension du modèle GM (1,1). Les performances de notre proposition sont évaluées et comparées avec les approches traditionnelles de suivi continu en considérant différents scénarios et profils de sujets. Les résultats révèlent que notre système offre un suivi efficace des sujets qui optimise la consommation des ressources du système en termes de calcul, énergie et réseau. Avec un minimum de volume de données collectées et traitées et un minimum de ressources utilisées, notre système réussit à assurer un suivi avec une précision élevée de l'évaluation du niveau de dépendance, d'apprentissage du comportement, de prédiction des conditions de santé et de détection de situation anormales.

Mots-clés : e-santé, AVQ, personnes âgées, contexte, dépendance, surveillance.

Title: Context-Aware e-Health Services in Smart Spaces

Abstract: In this thesis, we propose a new e-health monitoring system for elderly, dependent and isolated persons living alone. We provided a better understanding of the monitored person's context. We develop a context-aware framework for monitoring the person's activities of daily living (ADL) and consider the most famous scales applied in the dependency evaluation models used in the geriatric domain such as the Functional Autonomy Measurement System (SMAF). The proposed adaptive framework offers several services such as the collection of high relevant and contextual data and an evaluation of the health status (i.e. dependency level) of persons. The proposed approach allows learning the human's lifestyle regarding the achievement of the ADL and the detection of the behavioral changes that may represent a risk for the monitored person. In order get closer to real-life situations, we use a Markovian-based model built for generating long term and realistic scenarios. For the behavior detection and prediction, we propose a novel forecasting approach based on the extension of the Grey theory GM (1, 1). The performances of the proposed system are evaluated and compared to traditional monitoring approaches within different scenarios and persons' profiles. The results of our evaluations reveal an efficient monitoring that optimizes the system resources in terms of computing, energy consumption, and network. With a minimum of sensing data, our system succeeds to ensure a high accuracy regarding the evaluation of the person's dependency, behavioral patterns learning, prediction of the health condition, and the detection of abnormal situations.

Keywords: e-health, ADL, the elderly, context, dependency, monitoring.

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