Simon Klakegg

ENABLING AWARENESS IN NURSING HOMES WITH MOBILE HEALTH TECHNOLOGIES

UNIVERSITY OF OULU GRADUATE SCHOOL;
UNIVERSITY OF OULU,
FACULTY OF INFORMATION TECHNOLOGY AND ELECTRICAL ENGINEERING
SIMON KLAKEGG

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Abstract

This thesis explores the use of assistive in-situ technologies for formal caregivers in nursing homes. More specifically, focus is placed on improving context awareness and medication management. Although these topics have previously been researched for elderly care in general, few solutions targeting nursing homes have been generated. As the aging population further increases the burden on this care environment, it is important that solutions are found to help maintain care quality.

The main findings in this thesis emphasise how technology can assist formal caregivers and facilitate increased patient wellbeing. The articles presented in this thesis describe our creation of a context-aware sensor system (named CARE) and a non-expert miniaturised near-infrared spectroscopy (MNIRS) solution. Both systems were designed iteratively with the help of nurses and were evaluated in a nursing home. CARE quantifies elderly residents’ behaviour, analyses the resulting data and produces valuable and actionable insights for nurses. Results from a two-month-long user study demonstrate that the system can facilitate increased awareness of patients’ needs and enhance care service. The custom MNIRS solution allows nurses to scan pharmaceuticals and obtain accurate identifications. This method significantly outperforms currently available tools in nursing homes and represents a promising solution that can reduce medication mismanagement.

In the discussion section of the thesis, we revisit the research questions defined in the introduction and examine how each were answered. In addition, we discuss the augmentation of nursing home technology and various stakeholders’ perspectives. We then highlight how the work covered in this thesis was conducted in collaboration with industry and offer some conclusions, limitations and reflections.

Keywords: data analysis, near-infrared spectroscopy, nursing homes, sensors, technology
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Tiivistelmä
Tämä väitöstyö tutkii paikkasidonnaisten teknologioiden käyttöä hoitajien työn helpottamiseksi vanhusten palvelukodeissa. Työn keskiössä on erityisesti kontekstitietoisuuden lisääminen ja lääkehoidon valvonta. Näitä aiheita on tutkittu laajalti aiemminkin, mutta aitoihin ympäristöihin keskittyviä ratkaisuja on vielä vain vähän. Väestön ikääntyminen aiheuttaa haasteita vanhustenhoitossa, ja siksi on tärkeää kehittää ratkaisuja hoidon laadun ylläpitoa varten.


Väitöstyön keskusteluosuus palaa tutkimuskysymyksiin ja selventää, kuinka tehty työ ja saavutetut tulokset vastaavat niihin. Lisäksi keskustelu antaa yleiskuvan eri osapuolien näkemyksistä kehitetyyn ratkaisun hyödyistä ja sen soveltuvuudesta käytännön työhön. Lopuksi väitöstyö luo katsauksen yhteistyön rooliin eri osa-alueiden toteuttamisessa ja esittää kriittisen näkökulman työn puutteisiin sekä yhteenvetoon.

Asiasanat: data-analyysi, hoitokoti, lähi-infrapunasektroskopia, sensoriteknologia
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Oslo, November 2018

Simon Ytterbø Klakegg
**Abbreviations**

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<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AAL</td>
<td>Ambient Assisted Living</td>
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<tr>
<td>AWS</td>
<td>Amazon Web Services</td>
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<td>BLE</td>
<td>Bluetooth Low Energy</td>
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<td>EHR</td>
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<td>et al.</td>
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<td>IoT</td>
<td>Internet of Things</td>
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<td>exempli gratia</td>
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<td>HDMI</td>
<td>High-Definition Multimedia Interface</td>
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<td>ICT</td>
<td>Information and Communication Technology</td>
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<td>MNIRS</td>
<td>Miniaturised Near-Infrared Spectroscopy</td>
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<td>NFC</td>
<td>Near-Field Communication</td>
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<td>NHS</td>
<td>National Health Service</td>
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<td>NIRS</td>
<td>Near-Infrared Spectroscopy</td>
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<td>OS</td>
<td>Operating System</td>
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<td>QR</td>
<td>Quick Response</td>
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<td>Radio Frequency</td>
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<td>RFID</td>
<td>Radio-Frequency Identification</td>
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<td>RSSI</td>
<td>Received Signal Strength Indicator</td>
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<td>SDK</td>
<td>Software Development Kit</td>
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<td>SUS</td>
<td>System Usability Scale</td>
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<td>UI</td>
<td>User Interface</td>
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<td>VR</td>
<td>Virtual Reality</td>
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<td>WSN</td>
<td>Wireless Sensor Networks</td>
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Original publications

This thesis is based on the following publications, which are referred to throughout the text by their Roman numerals (I-V):


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1 Introduction

1.1 Background and motivation

An increasingly prominent concern for healthcare systems in a multitude of countries is the aging population, which is being caused by improved life expectancy over the last few decades (Lindgren, 2016). By 2030, 25.6% of the EU’s population is projected to be elderly (up from 17.4% in 2010) (Chłoń-Domińczak, Kotowska, Kurkiewicz, Abramowska-Kmon, & Stonawski, 2014). Thus, the diminishing proportion of working-age individuals will lead to a surge in the old age dependency ratio (Colby & Ortman, 2017). In 2009, the average long-term public care costs for Organisation for European Economic Co-operation countries comprised 1.4% of the gross domestic product, a figure which is expected to double by 2050 as the number of elderly citizens increases (Indicators, 2015). A report that explored demands in the future healthcare workforce predicted a global scarcity of 12.9 million caregivers by 2035, with a present deficit of 7.2 million (Truth, 2013). The same report also discussed potential solutions for this problem, paramount among them being innovative technology. Nurses working in elderly care are experiencing a growing work burden (e.g., stress, high workload), which has in turn resulted in declining work satisfaction, occupational burnout and high turnover rates (Engström, Ljunggren, Lindqvist, & Carlsson, 2006). Consequently, the elderly care service has experienced a large influx of new temporary personnel (e.g., students, rotating nurses). This is a problem, as temporary workers possess an inadequate amount of experience and information about their patients, and as such the quality of care service is declining (Tzeng, 2002).

In European countries, approximately 30% of elderly individuals obtain care at home, while 20% receive care in residential institutions (Bank, 2006; Giannakouris, 2008). Hence, the aforementioned issues caused by the aging population will impact both home and residential care. Caring for the elderly is particularly strenuous, as they often suffer from numerous, and sometimes critical, health issues. For example, among 4156 European nursing home residents, 80% required assistance with daily living, and 30% were greatly impaired: Pain, depression, behavioural problems and complications caused by falls were common symptoms (Onder et al., 2012). Adding to this serious challenge are the high expenditures associated with medication errors (Economics, 2014). Drug waste costs the National Health Service (NHS) €339 million yearly (Trueman et al., 2010).
The ramifications go beyond monetary concerns – for example, 125,000 Americans die each year from medication errors (Benjamin, 2012). Nursing home residents are especially affected by medication errors, as polypharmacy is common among this demographic (Lavan, Gallagher, & O’Mahony, 2016). Lack of knowledge, inhibited cognition, flawed communication and information, and the improper filling of pharmaceutical boxes are just a few of the problems faced by care staff (Metsälä & Vaherkoski, 2014).

Technology is now a focal point for researchers, who are seeking to use technological tools as a means to alleviate the imminent burdens mentioned above. Increased innovation in digital healthcare is spurring the development of new beneficial applications and tools. For example, sensors (Abbate, Avvenuti, Corsini, Light, & Vecchio, 2010) paired with smartphones (Lee, Jeong, & Yoon, 2012) can be used to increase awareness of elderly needs and improve care service. While there exists some related work in the field of context-aware systems for nursing homes, there remains a need for a replete tool that can provide nurses with all the required functionality. To achieve this, the first objective was to understand how to measure information units (defined as care metrics in this thesis) that are most relevant in elderly care service. Next, it was important to explore the ways in which care metrics could be communicated to nurses as well as the advantages of utilising context-aware sensor systems in nursing homes. Also, new ways to identify pills can assist caregivers in their daily work (Cunha, Adão, & Trigueiros, 2014). Yet, there is still a demand for a highly accurate medication identification method in nursing homes. New technology, such as Miniaturised Near-Infrared Spectroscopy (MNIRS), may provide new methods for solving problems in this domain.

Addressing these issues comprised the objective of this thesis and the research on which it was based – namely, to improve care quality and medication management in nursing homes through assistive technology. Thus, the following research questions are addressed in this thesis:

**RQ1.** How can we quantify and communicate the wellbeing of nursing home patients by using unobtrusive technologies and contextually relevant care metrics?

**RQ2.** What are the benefits of integrating a context-aware sensor system in a nursing home?

**RQ3.** What causes medication mismanagement in nursing homes, and how can we reduce problems associated with non-expert MNIRS?
1.2 Articles, contribution and author’s role

Five original articles are discussed in this thesis, four of which have been published (with one under review) in relevant peer-reviewed, international conferences in the Ubiquitous Computing and Human–Computer Interaction field.

**Article I** presents a system, part of a context-aware sensor system named CARE, designed to assist nurses working in residential care facilities. The primary objective of the system is to raise awareness about elderly patients’ needs. We conducted multiple field studies to determine what information the system should contain. A set of 18 care metrics were identified, which we defined as units of information that may be measured and observed as part of elderly care work practices. We evaluated the care metrics with nurses, and subsequently ranked them by level of importance. We then built an app that could inform nurses about these care metrics (the technical details of the sensor infrastructure used to measure the care metrics are introduced in Article II). The system also contained qualitative information on patients’ medical background, family and personality. To support nurses’ work during daily handover meetings, the system can input assessments of metrics that are hard to measure using sensors. We designed the system iteratively and kept the nurses involved in the process through interviews and user studies. The total time spent on user studies and interviews was seven days and involved eight caregivers. The final system received positive feedback, indicating that the nurses became more efficient and made more informed decisions in their daily tasks using the system. The nurses also appreciated how the system could be used as a source of information for new workers and for identifying long-term behavioural changes in patients. The author of this thesis led the work involved in designing and conducting the study, analysing the data and creating the system (with the help of the co-authors).

**Article II** presents an assistive healthcare platform named CARE (a context-aware sensor system), with a focus on sensor infrastructure that can capture data (e.g., activity, location) on residents of an elderly nursing home. The sensor infrastructure is the hardware that provided the data for the app in Article I. The primary objectives discussed in the article were to conduct a requirement elicitation for the hardware needed to realise the system. Also, we explored how the equipment could be installed in a collaborative care centre and conducted a proof-of-concept implementation (two-week duration) to verify component compatibility. As the nursing home strived to distinguish itself from a hospital setting, some technologies were considered invasive (e.g., video monitoring, electrocardiography,
Accordingly, we emphasised the usefulness of small, lightweight, rugged sensors, which can be attached to patients' shoes or to pouches as assistive aids. As the sensors have a long battery life (> 1 year), they are ideal for longitudinal deployment \(i.e.,\) no high maintenance requirements. We showcased how the sensors, along with the related infrastructure \(e.g.,\) automation units, displays) could be installed in a nursing home. Additionally, we discussed how these devices could contribute to a context-aware elderly care facility. The author of the thesis led the work involved in designing and conducting the study, including interconnecting and testing the hardware (with the help of the co-authors).

**Article III** presents our work in deploying the context-aware sensor system \(i.e.,\) CARE in a collaborating care centre. We actualised and implemented all system components, building on findings from Article I and Article II. The system was deployed for two months, during which time we collected data from 31 users (14 patients and 17 nurses) in the care centre. The collected data were analysed in the cloud, and daily summaries were calculated and displayed in an Android app designed for the nurses. A key objective was to examine how the system impacted the workflow of the nurses. Also, we sought to understand the sociocultural context of the care centre through a *post-hoc* data analysis. With the assistance of a data-driven tool, the nurses became more aware of patients’ behaviour and the amount of attention they received. They also found the handover function useful and felt that the system could act as an information hub. This indicates that the system could improve care planning and awareness of elderly needs. General feedback on usability and functionality were positive. The author of the thesis led the work involved in building and deploying the system, including collecting and analysing the data (with the help of the co-authors).

**Article IV** presents a non-expert assistive solution (enclosure and software) for MNIRS. The solution was designed to enable the commoditised use of MNIRS technology, such as administering medication in nursing homes. We observed in Article III the need for a semi-autonomous *in-situ* medication identification tool in the nursing home (examined in more detail in Article V). To inform the design choices for our non-expert solution, we first explored the impact of user-induced errors on the accuracy of MNIRS scans. Furthermore, we examined the complexity of analysing MNIRS scans and how such complexity impacted usability. These tests were necessary, as the hardware has traditionally been restricted to trained personnel in laboratory settings. Based on the findings from our study, we built an enclosure (3D-printed) for the device which was designed to alleviate the identified sources of user-induced noise. Next, we created an Android app that connected to

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the device and guided the user on the scanning procedures. It also automatically analysed and presented the results of the scans. To evaluate the proposed solution, we conducted a user study with 14 novice users, who were asked to scan a set of objects with minimal instructions and interpret the results from the app. Based on our findings, we concluded that non-experts could successfully use MNIRS, with an appropriate assistive solution. This opened up many interesting use cases, such as pharmaceutical identification in elderly care. The author of the thesis led the work involved in managing the tests, building the assistive solution (app and enclosure) and conducting the study (with the help of the co-authors).

Article V presents a pharmaceutical identification tool for residential elderly care using MNIRS. Before developing the system, we examined the current medication procedures in the selected nursing home and assessed how MNIRS could be incorporated into these procedures. We identified the need for a highly accurate tablet identification method and, consequently, assessed the performance of MNIRS for pharmaceutical analysis. A set of preprocessing and machine learning algorithms were benchmarked for this purpose. The best combination achieved 100% accuracy in pharmaceutical classification. The final tool utilised this model in combination with the assistive solution from Article IV and deployed it in a local nursing home for evaluation. The nurses who participated in the study were asked to identify a set of pills using both the existing method and our proposed method. Nurses were 46.25% more accurate in identifying pharmaceuticals using our MNIRS solution compared to the existing method used in the care centre. This strongly indicates that the new technology could serve as an efficient means to alleviate some of the problems related to medication errors in elderly care. The total time spent on user studies and interviews was five days and involved 13 caregivers. The author of the thesis led the work involved in conducting the study, including collecting and analysing the data, as well as evaluating the solution (with the help of the co-authors).

1.3 Thesis outline

The rest of the thesis is structured as follows: Chapter 2 contains related work, beginning with a definition of the broad challenges accompanying elderly care. In this chapter, we highlight how the aging population is causing increasing demand for healthcare providers. Furthermore, we investigate how nurses work in this difficult environment (e.g., characteristics of their workflow) and the issue of medication mismanagement. The next section examines the implementation areas
and categories of elderly care technology. We then explore previous systems implemented in elderly care, both general (pervasive) and residential care. The last section of related work explores solutions for assisted medication distribution, in-situ methods for pharmaceutical identification and the analysis of objects with MNIRS. Chapter 3 presents the research objectives, contributions and experiments in the five articles included in this thesis (with a summary table in the chapter introduction). The chapter is divided into three sections based on our research questions: quantifying and communicating the wellbeing of nursing home patients via unobtrusive technologies and contextually relevant care metrics (RQ1); the benefits of integrating a context-aware sensor system (i.e., CARE) in nursing homes (RQ2); and the causes of medication mismanagement in nursing homes as well as ways to reduce such problems with non-expert MNIRS (RQ3). Chapter 4 discusses the research questions, the augmentation of nursing home technology, various stakeholders’ perspectives, impacts beyond academia, and limitations of and reflections on the work in this thesis. Chapter 5 concludes the thesis.
2 Related work

In this chapter, we start by highlighting some key issues affecting caregiving, nursing workflow and medication mismanagement. Thereafter, we present an overview of elderly care technology and how it has been implemented in two contexts (pervasive and residential care). Lastly, we explore solutions for assisted medication distribution, *in-situ* methods for pharmaceutical identification and the analysis of objects with MNIRS.

2.1 Caregiving

This section starts by introducing some broad challenges in caregiving as well as their consequences. We then examine the complexity of caregivers’ (we focus on formal caregivers in this thesis) workflow and issues with medication management. These topics encompass the high-level issues we aimed to address with the thesis, namely decreasing care quality, lack of patient awareness and the large number of medication errors that occur in elderly care.

2.1.1 Aging population

As global life expectancy has steadily increased in recent decades, healthcare systems worldwide have experienced rising demand (Lindgren, 2016). For example, by 2030, one in five Americans will be 65 years of age or older. Consequently, the old age dependency ratio is calculated to surge, since the working-age population will be unable to sustain such growth (Colby & Ortman, 2017). Meanwhile, in Europe, public long-term care expenses averaged 1.4% of the gross domestic product of Organisation for European Economic Co-operation countries in 2009, a percentage which is estimated to double by 2050 (Indicators, 2015). Both the Global Health Workforce Alliance Secretariat and the World Health Organization have forecast a global shortage of 12.9 million caregivers (currently 7.2 million) by 2035 (Truth, 2013). In the same report, cutting-edge technology was considered as a promising means to alleviate the adverse effects of an overburdened workforce. These effects include reduced work satisfaction among nurses because of high workload and stress, which can in turn cause occupational burnout (Engström et al., 2006). To compensate, care centres are turning to temporary staff (*e.g.*, students, rotation nurses), but this can lead to high turnover rates. Because of the constant
influx of new workers, caregivers lack vital patient-specific information and experience, which results in a lower quality of care for elderly adults (Tzeng, 2002).

Healthcare among elderly adults in Europe can be categorised as follows: 30% home care, 20% institutional care and 50% without formal care (Onder et al., 2012). As the population continues to age, the strain exerted on both home and institutional care is anticipated to increase, and therefore innovative solutions are needed in both contexts. It is not only the large number of elderly adults that presents a challenge, but also the dire health problems they commonly suffer from. For example, a study of 4156 elderly adults living in European care centres revealed that disabilities were a frequent problem (Onder et al., 2012). Out of the 80% of residents who required help with their everyday routines, 30% was acutely impaired. These elderly residents also suffered from pain (36%), depression (32%), behavioural symptoms (27.5%) and falls (18.6%).

2.1.2 Workflow

Medical environments are dynamic and constantly changing (e.g., a nurse is administering drugs but is interrupted by a patient who falls). To compensate, caregivers frequently use shortcuts or workarounds (i.e., informal temporary practices for handling exceptions to normal workflow). Such dynamic changes in assignments were examined by Kobayashi, Fussell, Xiao and Seagull (2005) through models and ethnographies. More advanced and intelligent artefacts which could inform the user on the workarounds and improve planning were deemed necessary. A fundamental and essential event in nursing is the daily handover meeting, which is defined as:

“Transfer of professional responsibility and accountability for some or all aspects of care for a patient, or groups of patients, to another person or professional group on a temporary or permanent basis (Association, 2004).”

Previous work has labelled handover meetings as rapid, challenging and cryptic for novice caregivers (Payne, Hardey, & Coleman, 2000). Vital patient-related information (e.g., a patient had a stroke) is distributed and debated among the participants during handovers. As such, these meetings are considered critical to patient safety and are recognised by the World Health Organization as a top priority. Specifically, handover meetings are targeted in the High 5s (Leotsakos et al., 2014), a project which aims to address the preeminence of five central challenges to patient safety on a global scale.
Healthcare providers strive to implement Information and Communication Technology (ICT) to assist their staff (such systems and their benefits are examined in Section 2.2). However, caregivers frequently resist using the introduced technology. To avoid these types of failures and achieve user satisfaction, the primary adoption barriers must be identified and addressed when designing ICT systems (Lin, Lin, & Roan, 2012). Nurses’ opinions about the impact of ICT systems on patient care and workflow were surveyed by Ward, Vartak, Schwichtenberg and Wakefield (2011). In this study, realistic expectations and adaptive implementation and training procedures were considered decisive for the success of ICT tools according to the 1395 participants. Consequently, scientists should be more motivated to address these issues when deploying ICT systems in the future. Quantifying nurses’ workflow (location and activity) through direct observation revealed that a majority of their day-to-day assignments were labelled as short and frequent (Cornell et al., 2010). Also, the results suggested that the work context reduced subjects’ ability to plan care and think critically, which may in turn negatively impact the care service. The workflow of care personnel in social institutions (e.g., nursing homes, hospitals) shares similarities with a complex adaptive system (Vardaman, Cornell, & Clancy, 2012). The characteristics of these systems (e.g., non-linearity) should be addressed when designing new technology for successful future implementations. It is important to consider how a new tool will affect all functions of the caregiver, not just distinct components in their workflow.

### 2.1.3 Medication mismanagement

The erroneous distribution of medication dramatically impacts healthcare spending. An estimate of the cost of preventable medication errors by the NHS was in the €1.13 to €2.83 billion range (Economics, 2014). Another €339 million per year was attributed to drug waste (Trueman et al., 2010). An even more severe issue is medication mismanagement: One study determined that roughly 125,000 Americans die each year due to medication mismanagement (Benjamin, 2012). In an analysis of limitations related to medication error reporting in hospitals, the under-reporting of medication mismanagement was established as a fundamental issue (Hartnell, MacKinnon, Sketris, & Fleming, 2012). Significant costs are associated with avoidable drug-related deaths, while up to 20% of drug doses are wrongly administered in elderly care. Residents in nursing homes are particularly at risk of medication errors, as polypharmacy (i.e., a patient on multiple
medications) is common among the elderly (Lavan et al., 2016). To identify the primary challenges associated with medication mismanagement in elderly care, Metsälä and Vahekoski (2014) surveyed a large body of previous work. Their main findings implied that inadequate expertise, polypharmacy, wrongly filled medication bags, inhibited cognition and communication failure were some of the main issues.

2.2 Elderly care technology

This section starts by presenting implementation areas and categories of elderly care technology. This is important for contextualising the solutions we propose in this thesis. In the following sections, we first examine previous systems created for elderly care in general (pervasive); then, we reduce the scope to systems used in residential care – the target environment for the systems we have designed. Through this literature review, we recognised the lack of a supportive tool for caregivers in nursing homes, one which would include all the desired functionalities needed to raise awareness of patients’ needs (e.g., health analysis, context awareness, bios, notes, handover support).

2.2.1 Overview

Innovations in elderly healthcare technology research are heavily driven by the pressing burden of an aging population. New applications and assistive tools for both caretakers (formal and informal) and patients have been aimed at alleviating some of this pressure (Huttunen et al., 2017; Klakegg, van Berkel, Visuri, & Huttunen, 2017; Article I). As identified in a recent market report on technology for senior care, caregiving technology can be divided into four broad implementation areas (Figure 1) (Orlov, 2017). However, there is not always a clear distinction between these areas, and they all share similar elements (e.g., a wearable device with biosignal tracking and fall detection functionality bear similarities to both the ‘safety and security’ and ‘health and wellness’ groups).
Fig. 1. High-level overview of four implementation areas for caregiving technology (modified from Orlov, 2017).

Safety and security involve solutions that closely monitor elderly patients or automate their context e.g., fall detection, video monitoring and electronic locks (Abbate et al. 2010; Nasution & Emmanuel 2007; Markendahl & Laya 2013). In communication and engagement, we can find tools that enable social contact or immerse the user e.g., social robot, Facebook, Skype and games (Mordoch, Osterreicher, Guse, Roger, & Thompson 2013; Cota, Ishitani, & Vieira Jr. 2015). Health and wellness consist of services that measure and improve the wellbeing of the elderly e.g., iCare (Lv, Xia, Wu, Yao, & Chen 2010), Medisafe (Medisafe (2017), BeWell (Lane et al. 2014). Learning and contribution include resources that allow elderly adults to continue developing their skills and contributing to society e.g., e-learning modules (Weiner et al. 2014), Learn for Life (Life 2018), Virtual Reality (VR) training (Bisson, Contant, Sveistrup, & Lajoie 2007). The focus of this work is primarily on the health and wellness group, with components from the other groups.

A majority of the types of technology found in any of the implementation areas can generally be positioned in one of the following categories (modified from
Martínez-Alcalá, Pliego-Pastrana, Rosales-Lagarde, Lopez-Noguerola, & Molina-Trinidad (2016), with example references in each category):

- **Telehealth**: Use of ICT to enable remote health services (e.g., consultation, monitoring, alarm, education, rehabilitation) (Czaja, Lee, Arana, Nair, & Sharit, 2014).

- **Assistive Technology**: Technology that can support persons with disabilities or special needs, as well as the personnel who care for them (e.g., Ambient Assisted Living (AAL), VR assistance, home automation) (Blasco, Marco, Casas, Cirujano, & Picking, 2014).

- **Electronic Services**: Use of ICT to access digital content and information (e.g., e-learning, multimedia, entertainment, communication) (Botella et al., 2009).

- **Mobile Health**: Use of mobile technology for health and medical applications (e.g., wearables, sensing biosignals, health analysis and assessment) (Banos et al., 2014).

Similar to the implementation areas listed previously, these technology categories also have overlapping elements (e.g., a telemonitoring system may also be considered an AAL tool).

### 2.2.2 Pervasive care

There exist a wide range of health risks for the elderly that researchers have attempted to mitigate via ICT. For instance, small sensors can be integrated with everyday objects to enable fall detection in elderly housing (Abbate et al., 2010). This could be lifesaving, as falls are one of the major threats to the elderly (aged 65+) and are a frequent cause of death. Using patient location data from Radio-Frequency Identification (RFID) tags in clustering models has yielded promising results in terms of detecting outliers, such as abnormal behaviour (e.g., immobilised, not eating, not showering) (Hsu & Chen, 2010). These outliers can be symptomatic of underlying health issues, and nurses and family members can be notified when they are detected. Technology can also be valuable in areas that might not directly influence patients. Quantifying the workflow of nurses, for instance, can assist decision makers in exploring flawed task flows and inefficient time usage. Hence, activities and personnel behaviour can be improved, which can in turn lead to better care services for patients (Inoue, Ueda, Nohara, & Nakashima, 2016). Smart devices have numerous uses with regard to handling data (e.g., onboard sensors, high bandwidth internet, powerful CPU) (Luo et al., 2017; Opoku Asare et al., 2018).
and can act as an intermediate gateway for healthcare applications (Luo et al., 2016; Wac, 2012). For example, they can receive data from biosignal streams and analyse it locally, or they can offload the data to the cloud for computationally heavy processing (Lee et al., 2012). External services or third-party health apps may interface with these data to empower the user with detailed health information (Goncalves, Klakegg, van Berkel, & Hosio, 2018).

SensCare is an application that utilises the integrated sensors on smartphones to measure activity and inform the user through daily summaries (Wu, Peng, Zhu, & Zhang, 2011). This information can also be accessed by caretakers and doctors, providing them with data on the user’s health. These data could be lost without such apps, as elderly adults frequently have non-functional memory and cannot quantify their wellbeing. With emerging remote health systems, caring for patients is no longer restricted by physical proximity (Kvedar, Coye, & Everett, 2014). Different media, such as video streams, biological data and Electronic Health Records (EHRs) may be effortlessly distributed among care institutions and homes. The cost-efficiency of ICT indicates that it can be implemented to minimise healthcare expenditures (Aanesen, Lotherington, & Olsen, 2011). Telehealth can facilitate better use of resources, leading to improvements in the performance of care services (e.g., increased quality of care, improved user satisfaction, fewer visits to hospitals, lower consultation times). In scenarios were the elderly are living independently with the support of relatives or caregivers, telehealth may be particularly relevant.

### 2.2.3 Residential care

There has been a considerable influx of new assistive solutions targeting elderly individuals living independently in their homes. In comparison, assistive technologies for residential care have received less focus, despite their potential benefits for this environment (e.g., reduce costs, increase safety and efficiency) (Hall, Wilson, Stanmore, & Todd, 2017; Webster & Hanson, 2014). Additionally, a substantial amount of previous work has explored theoretical frameworks or scenarios. In this section, we examine sensor systems and other assistive tools that have been designed specifically for nursing homes. We primarily focus on tools for caregivers that are aimed at increasing awareness of patients’ needs by utilising data from sensor sources, omitting computer-based EHRs (Zhang, Yu, & Shen, 2012) and similar systems. Applications that interact directly with patients (e.g., social robots (Mordoch et al., 2013), VR assistive companions (Tsiourti, Joly,
Wings, Moussa, & Wac, 2014), and entertainment and communication tools (Bobillier Chaumon, Michel, Tarpin Bernard, & Croisile, 2014) were also excluded. CANoE is a context-aware framework for nursing homes (Nava-Muñoz & Morán, 2012) that notifies nurses through various media (e.g., phone, public display) when a patient event occurs. The notification message is augmented with information about the location and severity of the event and is assigned to caregivers based on availability. Aloulou et al. (2013) developed a nurse notification system using ambient sensors (e.g., proximity, vibration, pressure) and RFID tags. When abnormal behaviour (e.g., showering too long, falling) was detected among patients, nurses were notified about the event and could therefore intervene. The system can also perform simple health predictions using the data. Similarly, low-power sensors have also been utilised to successfully detect daily living activities (Kröse, van Kasteren, Gibson, & van den Dool, 2008). A study combining accelerometer values with Received Signal Strength Indicators (RSSIs) demonstrated how location-aware fall detection can increase patient safety in residential care facilities (Huang et al., 2010).

Vital-sign monitoring is another aspect of nurses’ workflow that can be improved with new technology (Chang et al., 2012). By using Wireless Sensor Networks (WSN), it is possible to automate the logging of values and automatically distribute vital data to the required third parties (e.g., family, doctor). A longitudinal study that collected activity data from wearables showcased how the data can be used to derive the health and functional level of the user (Merilahti, Viramo, & Korhonen, 2016). As mobile health services are becoming more prevalent, there is increasing demand for methods that can handle the generated patient data. A framework utilising cloud computing may aid in improved data processing and increased quality of health monitoring (Xu, Xu, Cai, & Jiang, 2014). Large nursing homes commonly host many residents, and it can be challenging for nurses to maintain an overview of each patient. Video monitoring has been validated as an efficient method for checking up on residents in remote sections (Sugihara, Fujinami, Jones, Kadowaki, & Ando, 2015).

A computerised decision support system for nursing homes has received positive feedback regarding its impact on care service (Fossum, Ehnfors, Fruhling, & Ehrenberg, 2011). An evaluation of a conceptual application for nursing homes cited benefits such as improved social connections, relationships and communication (Cahill, McLoughlin, & Wetherall, 2018). Webster and Hanson (2014) developed an interactive tool for caregivers with information about patients’ biography, family and pictures. In their evaluation, they received feedback on how
the tool could allow nurses to connect with and understand patients better. Also, the use of smart devices for note-taking can increase both the quality and frequency of user input compared to paper-based solutions (Pitts et al., 2015). Ultimately, by assessing all the aforementioned systems in this section, we can establish that the majority target specific use cases. Consequently, a replete tool which integrates all the necessary functionalities (e.g., health analysis, context awareness, bios, notes, handover support) for caregivers is missing.

2.3 Assisted medication distribution

This section starts by probing solutions for assisted medication distribution. To give adequate depth to the selected literature for this section, we examined solutions for healthcare in general (i.e., concentrating on elderly care, as the previous section would be too narrow). In the following sections, we survey work on in-situ methods for pharmaceutical identification and analysis of objects with MNIRS. Through the exploration of this body of work, it became apparent that a highly accurate in-situ pill identification method for caregivers was lacking. Also, we established that MNIRS could potentially be utilised for this purpose, but that its usability and performance needed to be measured.

2.3.1 Solutions

To alleviate medication errors, nurses have mentioned that improving current practices, implementing assistive technology (Article IV; Klakegg, Luo, Goncalves, Hosio, & Kostakos, 2016), enhancing patients’ medicine information sheets and better communication with doctors could be potential solutions (Ellenbecker, Frazier, & Verney, 2004). New applications have been developed to assist with these advancements. For instance, Medisafe is an app that enables efficient medication management by notifying and providing the user with support about medication ingestion (Medisafe, 2017). Chang et al. (2011) approached the issue through hardware, constructing a dispensing system for medicine with WSN technology. This smart pill box facilitates reminders, dispensing assistance and medication recording. Similarly, a combined solution consisting of a smartphone medication management app and an intelligent pill box has been demonstrated to benefit users’ medical adherence (Hayakawa et al., 2013). While a large portion of previous work has focused on supporting different functions related to smart medication dispensing or adherence, it is sometimes necessary to simply identify
individual tablets. Techniques that aim to reduce human errors in this process can be vital in efforts towards bettering medication management. Thus, in the following subsection, we explore different methods for identifying objects and pharmaceuticals (e.g., barcodes, machine vision, near-infrared spectroscopy, machine learning).

2.3.2 Pharmaceutical identification

Machine vision is a prominent method for computationally recognising objects, and its algorithms are under constant development to increase performance (Sonka, Hlavac, & Boyle, 2014). Each algorithm may be suitable for multiple or specific purposes, such as how the Hough Forest algorithm has been proven reliable for object tracking and recognition (Gall, Yao, Razavi, van Gool, & Lempitsky, 2011). Regardless, machine vision has still not achieved performance similar to that of a primate’s visual system (Geirhos et al., 2017). As an alternative to machine vision, hyperspectral imaging can enhance accuracy in situations where important information about the object must be found beyond the visible electromagnetic spectrum – for instance, to detect fungal infection in citrus fruit (Li et al., 2016). Researchers have also examined ways to enable human-like senses in machines, such as multimodal tactical sensing. Robots can now use vibration, force and temperature gathered from exploratory movements to recognise objects (Xu, Loeb, & Fishel, 2013).

The identification of pills at home and in healthcare settings has been aided by a variety of manual or assistive methods. For example, Pillbox is a database tool that allows users to input the physical characteristics of a pill and retrieve information and pictures of similar matches (Vardell, Goolab Singh, & Vaidhyanathan, 2011). Another method is to embed a reference picture and information about the correct tablet on the medication bag so that the user can verify whether the content is correct (Chen, Wang, Lin, & Chuang, 2013). Also, a barcode can be printed on the bag and scanned with a smartphone to retrieve data about the medication (Silva, Lopes, Marques, Rodrigues, & Proenca, 2013). While these methods can help identify a drug, they may not be able to determine who the receiver is. Thus, barcode medication administration software, which involves scanning a barcode on both the patient’s wrist and the pharmaceutical bag, can be utilised by nurses (Shah, Lo, Babich, Tsao, & Bansback, 2016). This programme verifies that the administration of medication is correct and can also check for dangerous drug interactions. A similar system using RFID tags (Peris-Lopez, Orfila,
Mitrokotsa, & van der Lubbe, 2011) and Near-Field Communication (NFC) (Alabdulhafith, Sampangi, & Sampalli, 2013) has also been developed.

The aforementioned approaches to pill identification and distribution may be susceptible to human errors (e.g., misinterpreting Pillbox results) or labelling errors (e.g., the wrong barcode on a medication). Consequently, in specific scenarios, it may be essential to accurately identify a specific pill based on its physical characteristics. As machine vision has performed well in many applications, it is now becoming more popular in the medication domain. It has recently been integrated with smartphone applications to enable quick in-situ identification of pharmaceuticals. The smartphone’s camera can be used to capture an image of the tablets, which can then be analysed using onboard processing power. The small form factor makes it ideal for mobile pill recognition among older adults. For example, Hartl, Arth and Schmalstieg (2011) used three visual variables (size, shape, colour) in their app to predict pill types. HelpmePills (Cunha et al., 2014) is another example of how pharmaceuticals can be identified using a smartphone app, thereby reducing medication errors. However, machine vision predominantly relies on visual features, which can lead to degraded performance when tablets are very similar in appearance. In comparison, MNIRS can infer the inner chemical composition of objects using hundreds of features. This enables highly accurate identification even for objects that are seemingly indistinguishable.

2.3.3 MNIRS

Near-Infrared Spectroscopy (NIRS) is an optical method that emits light in the near infrared region (wavelengths of 750 to 2500 nm) into samples. The attributes of the NIRS band enable the incident signal to penetrate deeper into the objects compared to visible light. The amount of light absorbed by the objects can be calculated from the reflected light. The vibrations of the atoms that comprise the object directly impact light absorbance, and it is therefore possible to infer the object’s chemical architecture from these data (Pasquini, 2003). Such absorbance features enable the complex and highly accurate analysis of samples. The application of devices utilising this optical method started around 1950 and has been increasing as hardware has been improved (Jha, 2010). The high accuracy of NIRS for detecting a variety of substances in materials has made it a popular tool for research. For example, it can be used to detect active substances in medicine and to identify pharmaceuticals (Dyrby, Engelsen, Nørgaard, Bruhn, & Lundsberg-Nielsen, 2002). Murkin and Arango (2009) used NIRS to study brain functioning in a clinical
setting. The technology can also be used to monitor food quality in industrial processing, as it has an unerring ability to compare mixtures or samples to a reference spectra (Huang, Yu, Xu, & Ying, 2008). Another implementation area is the classification of different types of gasoline based on the refinery or process by which it was produced (Balabin, Safieva, & Lomakina, 2010).

Ordinarily, NIRS requires large benchtop instruments in laboratories; but with advancements in optical hardware, this technology can now also be implemented in a mobile form factor. Instead of bringing the sample back to the laboratory, MNIRS can scan the sample in-situ. This accommodates a variety of exciting implementation areas, such as food research (Klakegg et al., 2016) and the examination of powder-based pharmaceutical excipients (Alcalà et al., 2013; Sun et al., 2016). We were interested in applying the analytical capabilities of MNIRS to in-situ pharmaceutical identification in nursing homes. However, MNIRS has not been evaluated for use by non-experts, such as nurses, and its performance has not been benchmarked for this specific purpose. These two important factors must be addressed before MNIRS can be integrated as a tool in nursing homes.
3 Research contributions

The research contributions from Articles I–V are presented in this chapter. In the first section, we describe which care metrics (i.e., patient-related information) are important in nursing homes and how they can be communicated through an Android app designed to assist nurses. Then, we highlight how a sensor system can ubiquitously measure these care metrics. In the second section, we explain how a data management framework can autonomously store, process and analyse all the sensor data. We next describe how the aforementioned components were actualised and integrated at full scale in a nursing home for two months. The context-aware system, which we named CARE, was evaluated to showcase how it could improve care service and generate new insights from patients’ and nurses’ data. We also compared CARE to other, similar systems. In the third section, we describe how MNIRS can be commoditised for non-expert users, such as nurses. We then discuss the need for highly accurate \textit{in-situ} pill identification in nursing homes. Thereafter, we demonstrate how we evaluated the performance of MNIRS for pharmaceutical classification as well as how it can be implemented to reduce medication errors in nursing homes. We also compare MNIRS to other, similar \textit{in-situ} pill identification methods. Together, this research contributes to understanding the potential of technology interventions that can facilitate an increase in patients’ wellbeing in a modern nursing home setting. Table 1 summarises each article’s research objectives, experimental setup and contributions relevant to this thesis. All the items in Table 1 help define the overall contribution of the thesis, namely two systems: a context-aware sensor system and a medication identification tool.

Table 1. Summary of research contributions.

<table>
<thead>
<tr>
<th>Article</th>
<th>Research Objectives</th>
<th>Experimental Setup</th>
<th>Contributions</th>
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<tbody>
<tr>
<td>I</td>
<td>Explore how to quantify elderly adults’ care needs in nursing homes. Evaluate how the quantified information can be communicated to nurses. Design and evaluate a mobile application that can assist nursing workflow.</td>
<td>Multiple field studies and visits to a local nursing home (1 week total). Observations, interviews and user studies.</td>
<td>Identified 18 distinct events, called care metrics. Sleep and activity were found to be the most important to the nurses (RQ1). An app displaying the care metrics, longitudinal data and related information can raise awareness of elderly adults’ needs (RQ1).</td>
</tr>
<tr>
<td>Article Research Objectives</td>
<td>Experimental Setup</td>
<td>Contributions</td>
<td></td>
</tr>
<tr>
<td>-----------------------------</td>
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</tr>
<tr>
<td><strong>II</strong> Conduct a requirement elicitation for a nursing home sensor infrastructure.</td>
<td>Proof-of-concept implementation (2 weeks).</td>
<td>Sensor systems in elderly nursing homes must be non-invasive and facilitate a home-like setting (RQ1).</td>
<td></td>
</tr>
<tr>
<td>Showcase how the sensors can integrate with a nursing home and verify the compatibility of devices.</td>
<td></td>
<td>Small, lightweight, location-invariant and rugged sensors with long battery life are ideal for monitoring the elderly in nursing homes (RQ1).</td>
<td></td>
</tr>
<tr>
<td><strong>III</strong> Implement and actualise all components of a context-aware sensor system for nursing homes.</td>
<td>System deployed for 2 months in a nursing home. Post-hoc data analysis, questionnaires and interviews.</td>
<td>A strategically placed sensor infrastructure combined with a data management platform can collect and analyse data autonomously without interfering with patients or nurses (RQ2). Conveying analytical insights from patients’ quantitative data to nurses can facilitate an increase in their awareness and enhance the care service (RQ2).</td>
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<tr>
<td>Analyse the sociocultural context through the collected data.</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Evaluate the impact of the system from the nurses’ perspective.</td>
<td></td>
<td></td>
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<tr>
<td><strong>IV</strong> Explore the feasibility of MNIRS in a non-expert setting (e.g., elderly care) and the impact of user-induced errors on scan accuracy.</td>
<td>Study of different scan conditions and samples. User study and interviews (3 days total).</td>
<td>Object placement and other interference sources have a significant impact on scan quality (RQ3). The complexity of the device and scan analysis have a negative impact on the usability of MNIRS (RQ3). Non-expert assistance (enclosure and software) can enable novice users (e.g., nurses) to successfully utilise MNIRS (RQ3).</td>
<td></td>
</tr>
<tr>
<td>Map the complexity and required knowledge to complete a full sample analysis.</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Design and evaluate a set of mechanisms to alleviate the aforementioned issues.</td>
<td></td>
<td></td>
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<tr>
<td><strong>V</strong> Examine the medication procedures in a nursing home and how MNIRS may be incorporated in the workflow. Validate the performance of MNIRS for pharmaceutical identification. Evaluate the utilisation of MNIRS for pharmaceutical identification in nursing homes through a user study.</td>
<td>User study, interviews, data analysis (5 days total).</td>
<td>A highly accurate in-situ pill identification method is needed in nursing homes (RQ3). MNIRS can identify a variety of different pharmaceuticals with 100% accuracy. Nurses using our MNIRS solution were 46.25% more accurate in identifying pharmaceuticals compared to existing methods (RQ3).</td>
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3.1 Quantifying and communicating the wellbeing of nursing home patients by using unobtrusive technologies and contextually relevant care metrics

In this section, we present the research contributions from Article I and II, which are summarised in Table 1. The work in this section was important, as it enabled us to identify the most relevant care metrics (i.e., patient-related information) for the assistive nursing home system. We focused on patients’ wellbeing, which can be defined as:

"The state of feeling healthy and happy."¹

Many factors may impact an elderly person’s wellbeing, such as social engagement, activity, hygiene, illness and nutrition (Doumit & Nasser, 2010). As derived in the formative study in Article I, caregivers in nursing homes tend to the wellbeing of residents, and thus we use wellbeing in the thesis. We also iteratively designed the app for the nurses to inform a User Interface (UI) which could communicate the care metrics in the most efficient and understandable manner possible. Lastly, to successfully measure patients’ and nurses’ behaviour in a nursing home, we selected and verified the appropriate sensor infrastructure. This was key to ensuring the integration of the CARE system with the target environment.

3.1.1 Care metrics

To develop the context-aware system for the nurses, we first had to determine what information it would contain. The objective was to deploy the system in a local nursing home, so it was crucial that our solution provided value to the nurses so it would be adopted as part of their workflow. As part of the work in Article I, four researchers observed daily practices in the nursing home over the course of three days. In addition, we used contextual inquiry and semi-structured interviews to discuss tasks and events that occurred during the study. This enabled us to find bottlenecks in the workflow, such as cumbersome tasks, which could be optimised using ICT. The nurses primarily cared for elderly patients (i.e., older than 65 years) with reduced health (e.g., poor mobility, dementia). Adopting common Human–Computer Interaction methodology (e.g., concept aggregation, affinity diagrams, note matching), we established 18 unique events that we labelled care metrics. A

¹ https://dictionary.cambridge.org/dictionary/english/well-being
A care metric is essentially an information unit that can be quantified or monitored as part of the elderly care service. Each care metric can be measured using either manual (e.g., Experience Sampling Method (Berkel, Ferreira, & Kostakos 2018)) or automated (e.g., sensors) methods, and its value may fluctuate throughout the day. Figure 2 contains the complete list of care metrics from Article I and how they may be visually represented.

![Fig. 2. Overview of the 18 care metrics and how they may be visually represented](reprinted by permission from Article I © 2017 Authors)

While the care metrics were derived through meticulous study, it was important to validate the significance of each unit. Hence, we visited the care centre once more and asked the nurses to rate each metric on a five-point Likert scale, depending on how important it was in their work. The context of each icon was explained briefly, so that all participants had a common understanding of their meanings. We sorted the results based on the mean score of each metric, and the resulting list had a substantial spread from the most to least important metric (Table 2).

**Table 2. Importance of care metrics ranked on a five-point Likert scale. The grey columns indicate care metrics which were used in later stages of the CARE project (reprinted by permission from Article I © 2017 Authors).**

<table>
<thead>
<tr>
<th>Care Metric</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sleep</td>
<td>4.75</td>
<td>0.46</td>
</tr>
<tr>
<td>Activity</td>
<td>4.62</td>
<td>0.74</td>
</tr>
<tr>
<td>Toilet</td>
<td>4.5</td>
<td>0.53</td>
</tr>
<tr>
<td>Eye Drops</td>
<td>4.37</td>
<td>0.91</td>
</tr>
<tr>
<td>Location</td>
<td>4.28</td>
<td>0.75</td>
</tr>
<tr>
<td>Food</td>
<td>4</td>
<td>0.92</td>
</tr>
<tr>
<td>Drink</td>
<td>4</td>
<td>0.92</td>
</tr>
<tr>
<td>Temperature</td>
<td>3.87</td>
<td>1.12</td>
</tr>
<tr>
<td>Heart Rate</td>
<td>3.75</td>
<td>1.03</td>
</tr>
<tr>
<td>Checkup</td>
<td>3.62</td>
<td>1.59</td>
</tr>
<tr>
<td>Care Metric</td>
<td>Mean</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>---------------------</td>
<td>------</td>
<td>-------------------</td>
</tr>
<tr>
<td>Microphone</td>
<td>3.37</td>
<td>1.5</td>
</tr>
<tr>
<td>Last Moved</td>
<td>3.37</td>
<td>0.74</td>
</tr>
<tr>
<td>Medicine</td>
<td>3.37</td>
<td>1.59</td>
</tr>
<tr>
<td>Diaper</td>
<td>3.25</td>
<td>1.9</td>
</tr>
<tr>
<td>Socialising</td>
<td>3</td>
<td>1.41</td>
</tr>
<tr>
<td>Calendar</td>
<td>2.87</td>
<td>1.45</td>
</tr>
<tr>
<td>Shower</td>
<td>2.62</td>
<td>1.59</td>
</tr>
<tr>
<td>Mood</td>
<td>2.37</td>
<td>1.3</td>
</tr>
</tbody>
</table>

Sleep was the highest-rated metric due to its perceived usefulness as a proxy for the patients' wellbeing. It was also challenging for the nurses to track sleep at night without disturbing the residents. Activity was deemed useful, as it indicated whether a patient was getting enough exercise. Care personnel sometimes forget events that happen sporadically (e.g., toilet, eye drops), so these metrics could serve as an essential reminder for them. When the health of patients starts to deteriorate, it can affect their food and drink behaviour, so the mean ratings for these metrics were in the higher range. While monitoring temperature and heart rate did not fit the home-like context of the facility, these metrics were still perceived as valuable. Diaper and shower were the two care metrics located in the lowest end of the table, as they are already tracked using pen and paper methods. The nurses perceived socialising and mood as too irregular to track, since these metrics could fluctuate wildly on an hour-to-hour basis. We noted that some of the care metrics could be more beneficially depicted in the form of graphs using longitudinal data, as doing so could reveal crucial trends (e.g., depression, isolation). Selecting a set of care metrics in Article I was necessary, as the design of the assistive app and sensor infrastructure was informed by these findings. Although we started with 18 care metrics, the grey columns in Table 2 indicate which metrics were used in the later stages of the CARE project. These were selected because they were essential and technically viable for sensing using unobtrusive wearables. We included mood, since some nurses indicated in the interviews that it was an exciting care metric. In the next section, we detail how we designed the app for the nurses.

### 3.1.2 CARE mobile application

As part of the work in Article I, we also created an Android app for CARE that could assist nurses and inform them about the care metrics. We first created high-fidelity sketches of the UI and asked the nurses to reflect on the design and
presentation of the information. The UI (final design can be seen in Figure 3) consisted of a main view with a list of all patients, with corresponding pictures, names and up to four care metrics that required attention. Each patient tile could be pressed, which, upon doing so, would open a view with more specific information on that patient (e.g., medication, family members, personality). The core concept of the app is to provide nurses with easy-to-understand and relevant information about the patients’ care needs.

In the second design iteration, we created a prototype Android app which was evaluated using the think-aloud protocol and semi-structured interviews. The think-aloud method enabled us to understand the nurses’ thoughts as they examined the UI. The initial feedback we received was positive, with the caregivers highlighting that value of the app as an in-situ tool. A PC-based system with patient information was available, but it was considered cumbersome to use, as it was located in a separate office out of proximity to patients. When we probed the nurses on the perceived value of the tool, we received feedback on its usefulness. For example, new care workers could easily learn more about patients through the various tabs in the application (e.g., medication, personality, health history). The main view provided a simple status overview of all residents, and the available information could be used to facilitate an increase to patients’ wellbeing. Furthermore, the participants appreciated the simple layout, with its clear and concise information. Throughout the evaluation stages, we received feedback on elements that could be improved, such as more distinct care metric icons and text (e.g., font colour could change depending on urgency) and the ability to add notes for residents.

For Article I, we also created the final app for CARE (Figure 3) based on the feedback from the prototype evaluation. The default main view contains a scrollable list with the picture, name and up to four care metrics for each patient. A care metric is shown when the data framework (detailed in a later section) processes the data and calculates a value which is below a predefined threshold. The handover mode is enabled from the top-right corner in the main view and loops through all patients, presenting important data about their wellbeing. It also enables care workers to input an assessment (five-point Likert scale) of the general health, appetite and mood of each resident. These data can be challenging to collect using the wearable sensor solution we implemented, so a manual method was needed.
The medical tab opens when a patient is selected from the main view, displaying information about the patient’s prescription drugs, health records and allergies. Notes can also be added in this tab. The user can utilise the bottom navigation bar to move to the family tab (view not displayed), which contains a list of relatives with names, pictures and buttons for quick contact through text or phone call. Next is the personality tab (view not displayed), which details the patient’s likes, dislikes and biography. The final health history tab visualises longitudinal data for each care metric through graphs. These can be utilised to discover trends in the patient’s wellbeing, which may otherwise be challenging to discover on a day-to-day basis.

In Article I, we also conducted the last evaluation of the final app using a task-based think-aloud protocol, in combination with semi-structured interviews and the System Usability Scale (SUS). The results matched the previous evaluation round (i.e., easy to understand, information clearly presented, good functionality). We recognised some minor flaws, such as the UI response time being a bit slow, but participants nonetheless navigated the app effortlessly. The SUS score was 89.4, which implied that the app performed well concerning learnability and usability, and that the users were satisfied. According to the nurses, the app could have a positive impact on their work, since it provided them with relevant information.
3.1.3 Ubiquitous sensing in nursing homes

The data for the care metrics used in the system were collected through a context-aware sensor infrastructure or manual input. In this section, we explain how we identified the required hardware for CARE’s sensor infrastructure, as part of the work in Article II. Through our study at the nursing home, it was clear that the managers wanted to maintain a home-like setting. Technology such as video monitoring or medical devices (e.g., electrocardiography, galvanic skin response) were regarded as invasive. The desired solution would have to be ubiquitously embedded in the residential care environment, without being cumbersome to use or causing significant additional labour. Hence, the hardware should not have required substantial maintenance (e.g., charging of sensors, daily setup, repairs). We selected the hardware illustrated in Table 3 based on the aforementioned criteria.

Table 3. Overview of system hardware for CARE (modified from Article II).

<table>
<thead>
<tr>
<th>#</th>
<th>Device name</th>
<th>Details</th>
<th>Usage</th>
</tr>
</thead>
<tbody>
<tr>
<td>36</td>
<td>Estimote Sticker²</td>
<td>RSSI, accelerometer, 7-m range, 1-year battery</td>
<td>Tracks nurses, patients, bed usage</td>
</tr>
<tr>
<td>19</td>
<td>Estimote Beacon</td>
<td>Temperature, ambient light, 70-m range, 5-year battery</td>
<td>Measures ambient context</td>
</tr>
<tr>
<td>14</td>
<td>Remix Mini³</td>
<td>BLE, HDMI, Wi-Fi, USB 2.0, Android OS</td>
<td>Receives and syncs data to the cloud</td>
</tr>
<tr>
<td>1</td>
<td>Galaxy Tab A6</td>
<td>Wi-Fi, BLE, Android OS, 3-day battery</td>
<td>Runs the CARE app</td>
</tr>
<tr>
<td>18</td>
<td>Road ID</td>
<td>1.9 cm x 3.8 cm, water-resistant</td>
<td>Carry-on pouch for the Estimote stickers</td>
</tr>
<tr>
<td>1</td>
<td>Co-link</td>
<td>RF blocking bag</td>
<td>Holds unused nurse sensors</td>
</tr>
<tr>
<td>3</td>
<td>Asus 4G-N12</td>
<td>4G router</td>
<td>Internet access</td>
</tr>
<tr>
<td>4</td>
<td>TP-Link Extender</td>
<td>300 Mbps, 23-m range</td>
<td>Extends Wi-Fi coverage</td>
</tr>
</tbody>
</table>

The Estimote Stickers were chosen as wearable sensors due to their small size, low weight, resilient material and convenient Android Software Development Kit (SDK). They were inserted in Road ID pouches, which allowed them to be easily attached to patients and nurses. Estimote Beacons were also acquired to monitor the ambient context in the nursing home (data were not used for any purpose in the scope of this work). To receive the sensor data, we used multiple Remix Minis, a small Android PC that can run apps built using the Estimote SDK. A Galaxy Tab

² https://estimote.com/
³ http://www.jide.com/mini (now discontinued)
A6 was selected to run the nurse application. A Radio Frequency (RF) blocking bag (Co-link) was obtained to ensure that unused sensors did not broadcast data to the receivers. The connectivity of Wi-Fi in the nursing home was subpar, with frequent data losses, so we invested in 4G routers and Wi-Fi extenders to ensure adequate internet connection. As part of the design considerations in Article II, we sought to keep the burden of the wearables to a minimum for the users. The Road ID pouch can be attached to shoes, belts or other items that the users own (e.g., walking aids, wheelchairs), as the sensor does not need to be worn in a specific manner. The battery life is up to one year depending on the configuration, which means that minimal maintenance is needed. The casing also protects the Estimote Sticker from fall damage and water splashes, which in turn reduces the chance that repairs will be needed.

3.2 Benefits of integrating a context-aware sensor system in a nursing home

In this section, we present the research contributions from Article III, which are summarised in Table 1. We start by describing how the data framework of the system worked, as well as how it received, processed, analysed and synchronised data to the app. Then, we detail how the CARE system was integrated in a nursing home for a two-month user study. Essentially, the work described in these sections built on the findings from Article I and Article II. Lastly, we highlight some results from the user study and post-hoc data analysis and compare our system with other solutions.

3.2.1 Data management framework

Before we implemented the CARE sensor system at full scale, we had to develop the data management framework as part of the work in Article III. It was necessary to store, process, analyse, synchronise and monitor the data stream coming from all the sensors. The structure of the data management framework can be viewed in Figure 4. The sensors are located at the first level and broadcast Bluetooth Low Energy (BLE) packets using secure Universally Unique Identifiers (UUIDs) with nurses, patients, beds and ambient context data. Multiple Remix Minis were distributed throughout the nursing home to receive the sensor data. An Android app built using the Estimote SDK and AWARE (Ferreira, Kostakos, & Dey, 2015) was responsible for parsing the packets and offloading the data to the cloud. AWARE is
a mobile instrumentation framework which enables the app to continuously run in the background as a plug-in (i.e., avoids being stopped by the Operating System (OS) to preserve battery). Data are stored locally on the hard drive, and the batches are inserted (10 K records each batch) in 30-minute intervals to a MySQL server hosted on Amazon Web Services (AWS).

Figure 4. The data management framework presented in Article III (reprinted by permission from Article III © 2018 Authors).

Automated scripts written in R run on a separate server in AWS to preprocess and analyse the data. The scripts execute daily at 10:00 and output summaries which are presented as care metrics in the nurse app. Depending on the specific analysis, subsections of the data collected in the previous day and night (06:30–06:29, 24 hours) are used for the computations. The Remix Minis can sometimes be affected by problems such as dropped Wi-Fi connections or the power cord being unplugged.
by a resident. Thus, the R scripts run 3.5 hours after the data collection period has ended to recover synced data from lagging devices. Missing data may cause inaccuracies in the generated summaries, which also motivated the choice to limit the scripts to only execute daily.

The nurses’ assessments of the handover functionality of the app were stored in a MySQL table in combination with the care metrics. When an assessment or care metric was below a predefined threshold, it was synced to the nursing app to inform the nurses. A selection of care metrics (e.g., sleep, activity and socialising) were always displayed as graphs in the health history tab. A large number of devices were used for the deployment, and it was vital to monitor the status of each one (e.g., Wi-Fi connection, battery life, packets sent and received). A dashboard was created to provide a simple overview of the last time each device had synced as well as details regarding packet transmission. In addition, the R scripts were interfaced with Slack so we could examine the computations (e.g., model performance, care metric values, service upkeep). This data management solution from Article III was automated and required no involvement from the nurses, which was vital to avoid interfering with their workflow. Consequently, the nurses could focus on their work and only interact with the CARE system through the UI of the app.

### 3.2.2 Nursing home integration

We installed the CARE system in the collaborating private nursing home, which was approximately 440 square meters and accommodated 15 residents, as part of the work in Article III. The left wing of the facility can be viewed in Figure 5, with example positions of the hardware.
The 14 Remix Minis were positioned both in public (e.g., lounge) and private (e.g., patient room) areas in the nursing home (Figure 6) to receive packets from the sensors. As the nursing home wished to maintain a home-like setting, it was important that the selected hardware had a small form factor and could easily blend in with the environment. Additionally, if the hardware was ubiquitous, the residents would be less prone to fiddle with it (e.g., remove the power cord, move the device).

The 4G routers and extenders were also distributed throughout the facility.

Fig. 5. Overview of one housing unit (left of dashed line), lounge area (top of dashed line) and kitchen (bottom of dashed line). Example hardware positions are marked in red (reprinted by permission from Article III © 2018 Authors).

Fig. 6. A) All Remix Minis and Estimote Beacons. B) Example position in the nursing home (reprinted by permission from Article III © 2018 Authors).
The wearable sensors were attached mainly to patients’ shoes; but in some cases, this was not feasible, so they were attached to their walking aids or wheelchairs instead (if used consistently throughout the day). This setup allowed us to monitor patients with minimal obstruction and intrusion. An overview of the wearable sensors from Article III can be seen in Figure 7, with placement examples. Some patients were curious about the introduced hardware but quickly adapted given its modest form factor. The Estimote Sticker was also small enough to be positioned in patients’ beds to monitor accelerometer events. We collected data for two months without any patients refusing to comply with the premises of the study. In a few cases, sensors would get lost (e.g., fall off, mixed in with laundry), but the monitoring system or nurses would eventually notice, and the sensors would be reattached.

![Fig. 7. A) Overview of sensors. B), C) Example positions on a patient and assistive tool](reprinted by permission from Article III © 2018 Authors).

The nurses also wore a Sticker Sensor, which enabled us to measure their interaction time with patients and other aspects of their workday. A nurse would retrieve a sensor from the RF blocking bag upon arriving at work and return it when leaving. We did not monitor individual nurses to preserve their anonymity and to minimise the number of sensors allocated to the project (i.e., no unique sensors for each worker). The nurses did not object to wearing the sensors, and it became a natural part of their routine. When the app was introduced to the nurses, we guided them through its functions. We also encouraged them to use the handover mode during their daily meetings and to input patient data (e.g., medical, biography) manually when possible.
3.2.3 Enhancing the care service

After collecting data for two months, we obtained a final dataset of 260 million rows, which contained all the sensor data. We were interested in further analysing these data as part of the work in Article III to uncover new insights into the sociocultural context of the nursing home. The first part of the post-hoc analysis explored participants’ (both nurses and residents) location data. The nursing home was divided into 19 geofences, and a random forest model was trained using RSSI values collected from each geofence. This model was used to predict a user’s location in the nursing home based on the wearable RSSI values. Consequently, we could measure how often patients were in proximity to a nurse (e.g., in the same geofence) and how much time patients spent around each other. We also examined the activity levels of each participant, including when the nurses were most active. We visualised the bed data for a set of patients and plotted the nurses’ assessments of patients’ appetite, health and mood.

We visited the nursing home to interview the nurses who had participated in the study. The objective was to evaluate how the system had impacted their work and their opinions on the application usage, as part of the work in Article III. We included the post-hoc analysis in the interviews so that the nurses could reflect on all the care aspects we had quantified (i.e., some analyses were omitted due to space limitations). It was apparent that the mean time nurses spent around patients heavily fluctuated throughout the day. It peaked around meal hours and reached its lowest point during the handover meeting. In comparison, the mean time nurses spent around patients per weekday was more stable. More alarming was the varying amount of time each patient spent with a nurse, since some residents were in proximity to nurses significantly less often than others. This was a big surprise to many of the nurses, who were not aware of this discrepancy in care treatment, as discussed in Article III. They stated that it was challenging to notice this discrepancy, as they did not quantify this type of information. The nurses also questioned whether they needed to change their workflow to resolve this issue.

With the activity data, we could identify the more independent and physically fit patients; we could also distinguish how hectic weekdays were for some nurses compared to others. The handover data (assessments of appetite, health and mood) were visualised for comparisons between patients. The nurses were surprised by how the values fluctuated between patients as well as how the data revealed changes that were not visible on a day-to-day basis. They also claimed that logging these data during handover facilitated a more detailed assessment. We also
circulated a questionnaire, and the results indicated that the nurses found value in using the tool. They were satisfied with its usability and ability to forecast long-term trends in patients’ behaviour. The results also indicated that the system enhanced the care service and encouraged care workers to continue using the system. We also received positive feedback regarding how the system worked as an information hub for users to update themselves when returning from vacation or sick leave. The care workers also suggested that the system could introduce a new preventive and data-driven workflow.

### 3.2.4 Comparison

Table 4 summarises previous research efforts towards creating assistive systems (predominantly sensor-based) for caregivers in nursing homes, based on the following properties:

- **Data Source**: the type of data that powers the system’s services.
- **Bio**: details on likes, dislikes, background, *etc.*
- **Health Analysis**: data-driven assessment of health status.
- **Notes**: textual input on care needs and status.
- **Context**: measuring activity, fall detection, tracking location, *etc.*
- **Interface**: allows clients to access information.
- **Handover**: supports the daily nurse meeting.
- **Evaluation**: controlled experiment, interview, think-aloud, *etc.*
- **Deployment**: a longitudinal user study.

These properties were derived based on our studies in the nursing home and key features in related systems, as detailed in Section 2.2.3. To the best of the author’s knowledge, this table contains the majority of related work in this distinct area. This systematic review indicates the lack of a tool that can integrate all the necessary functionality (*e.g.*, health analysis, context awareness, bios, notes, handover support). Thus, the CARE system addresses this gap in nursing home technology by integrating most of these properties.
Table 4. Overview of assistive technology for caregivers in nursing homes. (Parentheses indicate conceptual or partially implemented features).

<table>
<thead>
<tr>
<th>System Type</th>
<th>Data Source</th>
<th>Patient Notes</th>
<th>Nurse Interface</th>
<th>Family Interface</th>
<th>Handover Evaluation</th>
<th>Deployment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nurse Notification</td>
<td>Ambient Sensors</td>
<td>X</td>
<td>X (X)</td>
<td></td>
<td></td>
<td>24 10</td>
</tr>
<tr>
<td>(Aloulou et al., 2013)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Activity Detection</td>
<td>Ambient Sensors</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>(Kröse et al., 2008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Activity Monitoring</td>
<td>Wearable Sensors</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>60</td>
<td>23</td>
</tr>
<tr>
<td>(Merilahti et al., 2016)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DSS</td>
<td>EHR</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>(Fossum et al., 2011)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Framework (B. Xu et al., 2014)</td>
<td>Smart Devices</td>
<td>X</td>
<td>X</td>
<td>(X)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vital Sign Monitoring</td>
<td>Wearable Sensors</td>
<td>X</td>
<td>(X)</td>
<td>(X)</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>(Y.-J. Chang et al., 2012)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fall Detection</td>
<td>Wearable Sensors</td>
<td>X</td>
<td>(X)</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(C.-N. Huang et al., 2010)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nurse Notification</td>
<td>Wearable Sensors</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>(3)</td>
<td>(17)</td>
</tr>
<tr>
<td>(Navarro-Muñoz &amp; Morán, 2012)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>
In this section, we present the research contributions from Articles IV and V, which are summarised in Table 1. We start by describing how we enabled commoditised MNIRS use through a non-expert assistive solution (app and 3D-printed casing) in Article IV. This step was imperative for making this powerful analytical instrument accessible for caregivers in nursing homes. Subsequently, we detail the user study findings from Article V, which identified the need for a highly accurate pill identification method in nursing homes. Lastly, we demonstrate how we evaluated
the performance of MNIRS for pharmaceutical classification, and how the instrument can be implemented to reduce medication errors in a nursing home.

### 3.3.1 Enabling non-expert MNIRS

A large body of work has focused on benchtop NIR versions, which have been used since the 1950s (Jha, 2010). In contrast, few studies have explored the new generation of MNIRS devices or their scanning capabilities as identified in Article IV. To enable end users to adopt this powerful analytical tool, we had to examine the common issues that arise when it is used in a non-expert setting. Noise may be introduced to the system when a novice user interacts with the hardware. For instance, an inappropriately placed object or the shaking motion from an unsteady hand can affect the scan’s quality. To find a solution to these issues, we first identified the magnitude of a range of potential user-induced errors in Article IV. We first tested device motion, and it became apparent that even slight motion could cause inadequate scan quality. The sample would frequently lose contact with the device lens, which in turn created unwanted interference and lessened the amount of reflected light. Based on this result, we created an MNIRS casing designed to be positioned on a steady surface when scanning. We then tested how the scan quality changed when a sample was positioned at different distances from the MNIRS device. Various parameters (e.g., path loss, scattering) might lower performance when the sample is farther away. The test results indicated that the best distance is up to around 4 millimetres away from the lens. Based on these results, we designed the scanner casing to point upwards, which forced objects to be placed in contact with the lens.

The angle in which an object is positioned relative to MNIRS can also impact the light signal, so we measured the scan quality at angles from 0 to 50 degrees. The best results were achieved when the object was placed perpendicular to the lens (i.e., 0 degrees). Thus, a sample holder which accommodated this positioning was created and attached to the MNIRS casing. We also tested how scans were impacted by different object surfaces and discovered that uneven textures or edges could cause inadequate scan quality. This information was added to the scanning guide in the app (discussed later in this section) to prevent users from encountering this problem. As NIR light can penetrate a sample, it may interact with other objects positioned nearby; and in our tests, we discovered that this could cause interference. Consequently, we instructed users to only scan a single object at a time through the app. The last test in Article IV explored the effect of ambient light on scan quality.
The results indicated that higher light levels had a more significant impact, specifically when the object was transparent or not covering the MNIRS lens. Based on this, we added automatic light sensing to the app, with warnings for when high values were detected.

The casing we designed based on the aforementioned tests (Figure 8) was used to protect the scanner, reduce the magnitude of user-induced errors and assist in sample placement. The top lid (sample holder) can be changed based on the object type (e.g., pharmaceuticals or bread). This helps keep the sample in place and also guides object positioning via arrows and markings around the lens. The upwards-pointing design ensures that objects are placed in contact with the lens. The pharmaceutical sample holder walls are coated with insulating tape to reduce light scattering. This setup also allows the sample to be removed from its environment and placed on the machine without the chance of interference from nearby materials.

Fig. 8. Enclosure for MNIRS with a modular sample holder (e.g., can change between holders for pharmaceuticals and bread) (reprinted by permission from Article IV © 2017 Authors).

Besides correctly placing the sample and making sure the scan conditions are decent, the user also needs to initiate the scan and analyse the data. Traditionally, interacting with the hardware and conducting the analysis (e.g., preprocessing, machine learning) has been a complicated procedure. Thus, the assistive solution we designed should not only permit good sample positioning and ambient conditions but also simplify and automate MNIRS interaction. Users should not have to navigate advanced menus to configure the device and initiate scans. Consequently, in Article IV, we designed an Android app (Figure 9) to complement the MNIRS enclosure. The purpose of the app is to enable end users to interact with MNIRS more simply. Through the app’s UI, users can effortlessly set the desired
type of sample to be scanned. The app also provides simple instructions on the scanning procedure and information about the scan results. The scanned data are autonomously offloaded to the cloud, which preprocesses and analyses the data using pre-built machine-learning models. Hence, the user only has to start a scan, while the complex process of retrieving insights from the scan data is encapsulated from the user.

Fig. 9. Overview of the different UI elements for the assistive MNIRS app (reprinted by permission from Article IV © 2017 Authors).

We conducted a user study with non-experts to validate our solution. We quickly briefed participants on the technology before asking them to scan a set of objects
(with minimal guidance from the researchers). The results showed that participants could successfully scan and interpret the scan results using non-expert assistance (MNIRS casing and app). This indicates that non-experts can utilise MNIRS to scan objects with the appropriate assistive guidance presented in Article IV.

### 3.3.2 Medication management in nursing homes

A user study was conducted at a local nursing home to identify and examine what medication mismanagement issues existed there, as presented in Article V. We observed the workflow related to the administration of pharmaceuticals and carried out semi-structured interviews with the care workers. We discovered that all patient prescriptions were provided by a doctor based on a diagnosis. Caregivers in the nursing home update a medication list in the local system when a change occurs while also checking for drug interactions (e.g., dangerous combinations of pills). Medication is acquired by and distributed to each patient individually (i.e., there is no sharing of medications, and medications are stored in separate boxes), and the interval for ordering medications from the pharmacy is two weeks. Medications arrive in a single box per patient with multiple prescription bags inside (Figure 10 B), one for each day and time (i.e., morning, midday, afternoon, evening). Each bag is transparent and is labelled with the patient’s name, drug information, time, date and a scannable Quick Response (QR) code, which provides further information. The nurse working the nightshift arranges the medications for the next day and separates them per patient into one of four baskets, depending on the time slot allocation (Figure 10 A). Non-prescription drugs are stored in a joint basket with the patients’ names written on individual boxes (Figure 10 C).

![Fig. 10. A) Cabinet with four medication baskets, one for each time slot. B) Box containing prescription bags. C) Basket of non-prescription drugs (reprinted by permission from Article V © 2018 Authors).](image)
The nurses stated that they frequently needed to identify tablets in the prescription bags to verify the content or sort them further. This was achieved by scanning the QR code on the bag with a smartphone, which opened up a list with images and information about the pills. However, as the pills were visually similar, distinguishing between them with this tool was challenging. Although the nurses had to pass a medication management exam every three years, the pharmaceutical products changed more frequently, and the demanding work environment led to errors, such as distributing the wrong pill type (e.g., mixing tablets, tablets incorrectly sorted) or giving incorrect doses. Nurses also occasionally found tablets on the floor after meals, but without an accurate identification method, it was hard to backtrack to the intended recipient. These findings from Article V indicated the need for an accurate in-situ pill identification tool in the nursing home, one which could alleviate at least some of these issues.

3.3.3 Reducing medication errors with MNIRS

As we discovered the demand for a rapid and highly accurate in-situ pill identification method in the nursing home, we proceeded to evaluate the performance of MNIRS for this purpose. It was essential to establish whether the new generation of this hardware was suitable for use in a medical context. As part of the work in Article V, we acquired 20 distinct types of pharmaceuticals (Figure 11), which we scanned multiple times with MNIRS. A variety of preprocessing algorithms (savitzky–golay, standard normal variate, derivatives, background correction) were tested in combination with machine learning algorithms (naive bayes, K-nearest neighbours, random forest) on the scan data. Preprocessing removes noise in the scans and improves classification accuracy. The best option combined savitzky–golay, derivatives, standard normal variate, and naive bayes or random forest, achieving 100% accuracy in pharmaceutical classification using 10-fold cross-validation. A further exploratory analysis of the scan data, preprocessing and machine learning algorithms was conducted using principal component analysis, feature analysis and training score plots. The results indicated that MNIRS can capture a high level of detail about the pharmaceutical samples and achieve adequate performance for use in a medical context. We conducted a user study to evaluate our solution in a practical environment and compare it to existing methods in the nursing home. From the pharmaceutical set, we selected 10 pills to form five visually similar pairs (1-6, 2-7, 3-8, 4-9, 5-10, Figure 11), where the tablets in each pair were increasingly more challenging to distinguish from each another. We
mixed all the tablets into one group to simulate a scenario in which a pill bag contains several similar tablets and a nurse is required to separate them.

As part of the work in Article V, we asked the participating nurses to complete two tasks. In the first task, they had to identify the 10 mixed pharmaceuticals with the currently used method in the care centre. As established previously, this involved scanning the QR code on the prescription bag with a smartphone app. A list of all the tablets with pictures and information is then provided to the user, who must establish a visual match between a pill in the bag and a pill in the app to successfully identify it. In the user study, we provided the nurses with a replica of the original app, which was created in Android. In the second task, the participants used our MNIRS solution (the non-expert assistance displayed in Figures 8 and 9) to identify the tablets in the mix. Pseudo-anonymous markings were used on the tablets so we could track them without revealing them to participants. In this manner, we could compare the accuracy of the current method (i.e., task 1) with our proposed system (i.e., task 2). Identifying the tablets in task 1 was problematic for the nurses, who found it difficult to separate even the more visually distinct pills. An overall accuracy of 50% was achieved in task 1, and the resulting confusion matrix (‘Manual’ in Figure 12) was quite dispersed. In comparison, the accuracy in task 2
was 96.25% using MNIRS, and the confusion matrix (‘NIRS’ in Figure 12) had a clear diagonal trend. This indicated that MNIRS was a significant improvement over the existing method for pharmaceutical identification.

![Confusion matrix of user study classification results from task 1 (Manual) and task 2 (MNIRS)](image)

**Fig. 12.** Confusion matrix of user study classification results from task 1 (Manual) and task 2 (MNIRS) (reprinted by permission from Article V © 2018 Authors).

### 3.3.4 Comparison

In Table 5 we summarise previous research efforts towards creating *in-situ* pill identification methods for healthcare and compare them against MNIRS. These methods are discussed in more detail in Section 2.3.2. To the best of the author’s knowledge, this table contains the majority of related work in this distinct area. By inspecting the user interpretation level column, it is apparent that few methods have a low value (i.e., only machine vision and MNIRS). It is important to minimise user interpretation, as nurses often have inhibited cognitivity (Metsälä & Vaherkoski, 2014) and may misinterpret the medication identification results. As machine vision only relies on visual features (e.g., size, shape, colour, markings), it may exhibit degraded performance when tablets are visually similar. However, MNIRS, which uses hundreds of absorbance features for classification, represents a superior and novel method.
Table 5. Overview of some *in-situ* pill identification methods in healthcare (destructive methods not considered).

<table>
<thead>
<tr>
<th>Application Type</th>
<th>Method</th>
<th>User Interpretation Level</th>
<th>Features Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference (Vardell et al., 2011)</td>
<td>DB Query Tool</td>
<td>High</td>
<td>Visual</td>
</tr>
<tr>
<td>Reference (Chen et al., 2013)</td>
<td>Printed Pill Bag Image</td>
<td>Medium</td>
<td>Visual</td>
</tr>
<tr>
<td>Reference (Silva et al., 2013)</td>
<td>Printed Pill Bag Barcode</td>
<td>Medium</td>
<td>Visual</td>
</tr>
<tr>
<td>Reference, Linking (Shah et al., 2016)</td>
<td>Printed Pill Bag Barcode, Patient Barcode</td>
<td>Medium</td>
<td>Visual</td>
</tr>
<tr>
<td>Reference, Linking (Peris-Lopez et al., 2011)</td>
<td>Pill Bag RFID, Patient RFID</td>
<td>Medium</td>
<td>Visual</td>
</tr>
<tr>
<td>Reference, Linking (Alabdulhafith et al., 2013)</td>
<td>NFC Pill Bag, NFC Patient</td>
<td>Medium</td>
<td>Visual</td>
</tr>
<tr>
<td>Object Detection (Cunha et al., 2014; Hartl et al., 2011)</td>
<td>Machine Vision</td>
<td>Low</td>
<td>Visual</td>
</tr>
<tr>
<td>Object Detection</td>
<td>MNIRS</td>
<td>Low</td>
<td>Absorbance</td>
</tr>
</tbody>
</table>
4 Discussion

This chapter begins by revisiting the research questions defined at the start of the thesis and examining how they were explored. Next, we discuss the augmentation of nursing home technology and various stakeholders’ perspectives. We then highlight how this work has an impact beyond academia before concluding the chapter with some limitations of the work and some reflections on the thesis overall.

4.1 Revisiting the research questions

4.1.1 RQ1 - How can we quantify and communicate the wellbeing of nursing home patients by using unobtrusive technologies and contextually relevant care metrics?

The first objective of the CARE project was to establish the care metrics. As the nurses had never worked with technology such as the one we proposed, there existed some misconceptions about which care metrics were actually important. For example, we noticed that the ‘mood’ metric received low ratings in the first evaluation, but when presented in a longitudinal format (i.e., visualisation from multiple days of data) post-deployment, the nurses found it to be interesting. Regardless, the resulting set of care metrics from Article I provided a fundamental understanding of which care needs most influence the wellbeing of patients. After establishing the care metrics, we designed the CARE app for the nurses to view. As the nurses had some negative perceptions about an existing PC-based information system, we developed the app in a mobile format. Therefore, the system could be carried around in-situ and adopted in the workflow. By incorporating what the nurses perceived as valuable data in the tool, the chance of continued usage increased.

Numerous healthcare technology implementations fail because they do not involve the user in the design phase (Lin et al., 2012). We demonstrated that the system from Article I could inform nurses about important patient information and raise awareness about elderly needs. We first planned to collect sensor data for the care metrics using armband devices (e.g., FitBit, Jawbone). However, these would require frequent charging and would be explicitly placed on wrists, which was considered invasive. A fundamental requirement for our system in Article II was that it had to harmonise with the nursing home’s vision of being home-like (i.e., no
visible medical equipment, like in hospitals) and should not add more labour to the nurses. Thus, we selected small, lightweight, rugged sensors which had a long battery life and could be positioned freely on the residents.

4.1.2 RQ2 - What are the benefits of integrating a context-aware sensor system in a nursing home?

The sensor infrastructure combined with the data management platform was important for enabling autonomous data collection (i.e., required no nurse intervention) and analysis. Since the Remix Minis had a modest form factor, they blended in easily with the nursing home. We experienced few maintenance issues with the Estimote Stickers, and the participants did not mind wearing them. This solution allowed us to successfully collect data for the entire study (two months). The sensor and handover data complemented each other and quantified a broad range of residents’ care needs, and thus also their wellbeing. Through the evaluation in Article III, we received feedback on how CARE provided insights on care aspects that would otherwise go unnoticed (e.g., long-term changes in sleep patterns, activity). While the nurses stated that the system did not necessarily make them more efficient, they did believe that the care service was improved. Incorporating features that could better benefit rotating workers (e.g., qualitative patient information) proved invaluable for helping them to familiarise themselves with patients faster. The medication tab did not emerge as a frequently used function, which may be attributable to strict existing protocols – our app would need certification to replace these protocols. In contrast, the main screen was used by the nurses to obtain a brief overview of the current status of the nursing home. Also, the handover mode added structure and health assessment functionality to the daily meetings. Most of the limitations with regard to integrating CARE in the nursing home were technical, as is discussed in the limitations section. Use of the system was strictly optional, and thus the nurses used the system when there was an opening in their workflow. As the team of researchers closely monitored the hardware infrastructure, no extra burden was placed on the nurses.
4.1.3 RQ3 - What causes medication mismanagement in nursing homes, and how can we reduce the problems with non-expert MNIRS?

From observations and discussions with the nurses, we inferred common challenges in dispensing and administering medication. It was apparent that the nurses were not comfortable with the current method available for medication identification, as it involved a moderate amount of human error. We considered MNIRS as a solution to many of the issues the nurses experienced. The work conducted in Article IV was essential for enabling MNIRS use among non-experts, and the viability of the tool for users, such as nurses, was demonstrated. Furthermore, in Article V, we discovered how exceptional the device’s performance was for pharmaceutical classification. We combined these findings and designed a solution which was significantly more accurate than the existing in-situ pill identification methods in the nursing home.

We do not expect MNIRS to eliminate all types of medication errors in nursing homes. For instance, it cannot fix prescription errors that occur in pharmacies or replace the outdated medication sheets in nursing homes. However, it can be a helpful tool for in-situ tablet identification and for deterring the mismanagement of drug dispensing and administration. As MNIRS interfaces with an Android app, the potential of smartphones can be utilised to further the tool’s functionality. For instance, the app could interconnect with prescription databases, health records and even the CARE system to aggregate services into one place. This would simplify its use for nurses, thereby allowing them to focus more on caring for patients.

4.2 Augmenting nursing home technology

4.2.1 CARE

Today, elderly healthcare providers recognise the complications caused by the aging population (Lindgren, 2016). There is a shortage of care workers, which has led to an increasingly stressful and demanding care environment (Engström et al., 2006). In such an environment, awareness of patients’ needs may be diminished; worse, previous research has shown that the quality of the care service has been negatively impacted (Tzeng, 2002). Aging in place is an excellent option to lessen some of the burdens on residential care (Wiles, Leibing, Guberman, Reeve, & Allen, 2012). Naturally, much research has targeted assistive technology and telehealth to
support independent living. That said, a significant proportion of elderly adults still require care in a nursing home, as they cannot complete daily living tasks unassisted (Bank, 2006; Giannakouris, 2008). Nevertheless, there remains a lack of assistive tools for caregivers in nursing homes from a research perspective, which motivated the development of CARE.

When we compare CARE to existing systems (Table 4), it is apparent that many systems focus on a specific use case, such as monitoring patients’ activity, vital signs or falls. Also, previous studies have often been limited to controlled data collection and post-hoc analysis. In comparison, CARE involves a much more holistic approach, with many integrated functionalities (e.g., biography, health analysis, note-taking and context awareness about patients). Furthermore, we included the nurses’ context to monitor interactions with patients, which up until now was also uncommon. A few systems have provided an actual interface for the nurses to interact with, but the handover functionality is exclusive to our system.

Although we worked closely with a single nursing home, the system is by no means limited to use within this one facility. The infrastructure can be implemented in other locations; however, to do so, we would need to rebuild the models and divide the new spaces into geofences. The system’s functionality could also be useful in other application areas, such as childcare or school systems, to measure interactions between two parties or to explore how physical spaces are used. Since the sensor infrastructure requires little maintenance, longitudinal studies are also possible. That said, it is important to find suitable locations to position the sensors in these new use cases.

4.2.2 MNIRS

Medication errors are costly (Economics, 2014), fatal (Benjamin, 2012) and under-reported (Hartnell et al., 2012) in healthcare. These issues also exist in nursing homes, where a significant number of drug doses are incorrectly administered (Lavan et al., 2016). We have confirmed through both the relevant literature (Alabdulhafith et al., 2013) and our study in Article V that errors can happen at any stage of the medication process (e.g., prescribing, dispensing, administering). The nurses we interviewed lacked an automated and precise pill identification method; in response, we created the MNIRS solution. In Table 5, we compared the MNIRS solution to other portable in-situ pill identification methods (not considering dispensing boxes or destructible methods). It is clear that many of the systems rely on visual features, and therefore the level of user interpretation is considerable for
most. This means that users are not given a definitive answer about the identity of a pill using many of these tools. For instance, users might be provided with three pictures and then must decide which one looks the most similar to the tablet at hand. User interpretation can be reduced with the use of machine vision, as classification is automated. However, machine vision also relies on visual features and does not always achieve adequate performance. Hence, through our MNIRS solution, we have addressed the need for automated and highly accurate in-situ pill identification.

4.3 Stakeholders’ perspectives

In this section, we discuss various stakeholders’ perspectives and their relationship with nursing home technology. We start with a high-level overview and then narrow it down to the patients’ point of view.

4.3.1 Government

Policymakers’ primary objective is to alleviate broader global issues caused by the aging population (e.g., costs, understaffing, care quality) (Tak, Benefield, & Mahoney, 2010). From their perspective, technology is a means to achieve this goal. Hence, countries like Finland are committed to creating an environment for healthcare technology innovation and development, which is being achieved through public funding and supportive organisations (Health, 2018). The systems presented in this thesis were supported by such funding. As new systems are created for nursing homes, it is important that standards and regulations are put in place to ensure adequate performance. For instance, the MNIRS solution we developed is one example of a system that must undergo rigorous testing before being implemented. The CARE system should also adhere to a set of standards. This is challenging, as the field is rapidly changing and rules that are too rigid may curtail advancements (Vincent, Niezen, O’Kane, & Stawarz, 2015). Governments have an important duty to find the right balance between flexibility and regulation. Furthermore, their role in supporting care institutions that implement healthcare technology is imperative; one example of such support are Promoting Interoperability Programs (CMS.gov, 2018), which provide incentives to institutions that adopt EHRs. Additionally, decision makers must support changes to the structure of the care service, as technology accommodates new approaches to caregiving. For instance, the CARE system could be introduced as a fundamental tool for reflection and insight during handover meetings.
4.3.2 Management

Throughout the project, we were in contact with the management of the nursing home to maintain agreement on details regarding our studies and to discuss the potential outcome of the project. From their perspective, insights into the work conditions and environment of the nursing home were interesting. Instinctively, they wanted to increase the wellbeing of patients, but their main focus was on managing the institution. Information such as how active the nurses were and how much time they spent around patients could indicate whether the nursing home was adequately staffed. This information might also be used to make well-defined arguments in favour of receiving additional funding to hire more workers. In the future, nursing homes could define the acceptable levels for the quantitative care metrics. These could be assessed on a national level, which would enable the allocation of resources to where they are most needed as well as to detect misuse (e.g., employing too many workers). Furthermore, a data-driven workplace such as this could utilise dynamic staffing, as the number of nurses may fluctuate depending on the specific day or time. As some patients may require less attention (as revealed by the data), care providers could also offer flexible pricing, whereby the costs are adjusted relative to the amount of care received.

4.3.3 Nurses

The user generally decides whether a healthcare technology will be successfully adopted. Therefore, when designing tools for nursing homes, it is imperative to involve the caregivers in the process to achieve good user satisfaction (Lin et al., 2012). We continually evaluated CARE and the MNIRS solution with the nurses during their development to ensure that the end result matched their initial expectations. When we implemented CARE, the nurses were slightly hesitant and sceptical about the new technology. Particularly, more senior workers were uncertain about how the system could be incorporated into their workflow. The nursing students, who were completing their practice period, were more open to both CARE and the MNIRS solution, as the nursing programme now incorporates digital healthcare tools into the syllabus. This highlights the diverse background of the caregivers and how crucial it is to provide good introduction and guidance for new technology interventions. CARE was deployed for two months, and since the system was still in an experimental stage, unexpected errors occasionally occurred. This could have led to brief periods where erroneous data were fed into the app, so
it was essential to remind the nurses that this was normal, thereby avoiding the creation of any distrust. Naturally, for permanent implementation of CARE and MNIRS, the service must provide accurate and robust results.

### 4.3.4 Relatives

Healthcare technology may involve and impact the relatives of patients differently, depending on the context in which it is implemented. For instance, telehealth can support independent elderly living at home and can be utilised by family caregivers (i.e., informal caregivers) to monitor the patient and intervene when a critical event occurs (Chi & Demiris, 2015). In comparison, the CARE system we implemented was aimed at assisting caregivers in a nursing home with around-the-clock staffing, where the need for such family care interventions was nonexistent. This, however, does not exclude families as a valuable support mechanism for the elderly, but rather shifts their role towards social companionship. Two of the systems in Table 4 discuss the option of providing family members with an interface to access some of the patients’ data (e.g., vital sign monitoring, activity, health status). This would enable relatives to stay updated on the patient’s status and potentially motivate them to visit more frequently (e.g., if they notice that the patient is sick and want to provide moral support). Before this could be implemented, a study would be required to identify which data were appropriate to display. With CARE, we can facilitate quick communication with relatives through SMS or standard phone calls. We discussed the potential of a client app for relatives with the nurses, who mentioned that it could also be useful for informing families about administrative tasks (e.g., residents have bills to pay, need new clothes).

### 4.3.5 Patients

The technology solutions we designed were aimed at facilitating increased patient wellbeing. For instance, MNIRS attempts to reduce medication errors caused by nurses so that patients suffer less from adverse effects. Similarly, CARE facilitates an increase in nurses’ awareness of patients’ needs and improves the care they receive. While most healthcare technologies have noble intentions, it is crucial that none are implemented at the expense of patients’ rights. In this sense, the MNIRS device does not interact with the patient and may not require the same type of consent as the sensor usage implemented in CARE. Attaching devices to patients and monitoring their behaviour can be considered privacy invasion, so it is
important that the patients agree to the premises, especially when their cognitive reasoning is inhibited. Therefore, both caretakers and relatives should assess the appropriateness of the technology. We collaborated closely with a local elderly care foundation, which approved our study. The nurses and management of the nursing home were also thoroughly informed and agreed to the premises (nurses could opt out if they did not want to participate). Similarly, the patients and family members were also informed (participation was voluntary). Some patients had a tendency to move items randomly and as such could not have a Remix Mini in their rooms to prevent damage to the hardware. There was no refusal of consent that required management. The nursing home sought to maintain a home-like setting, and CARE was deemed suitable for this environment, since sensor integration was not perceived as obtrusive. However, in the future, we would like to experiment with various implementations of pervasive sensing and improve the form factor of the wearable device. As the CARE system stored sensitive patient data, it was important to use pseudo-anonymous identifiers for database entries. In addition, the data syncing was encrypted to keep it secure and private. The tablet was also secured with a PIN-code in case it got lost, and it was stored within a locked facility within the nursing home.

4.4 Impact beyond academia

The work discussed in this thesis was mainly conducted in an academic setting, and the results have been published in conference and journal proceedings. However, we remained in close collaboration with the industry throughout the study. In the CARE project, we worked closely with a local company (named Haltian Oy) that specialises in sensor hardware and software platforms for IoT. Haltian Oy is interested in opportunities related to sensing in nursing homes and how their products could be implemented in this setting. The CARE system was used as a case study to expand their business focus, and we are now working together on commercialising the system with more advanced hardware and a more extensive technical team. We aim to improve the system even further to make it more resilient, accurate and ubiquitous. In the MNIRS project, we involved key stakeholders in pharmaceuticals in hospitals. As the initial results were promising, we are now developing a better non-expert assistance system, tuning the algorithms for even larger scan libraries and aiming to deploy the system on a grander scale in a medical context. Ultimately, the end goal is to fully commodify both systems and reach a mass market.
### 4.5 Limitations and reflections

The studies presented in this thesis were primarily conducted at one nursing home. Although the nursing home is part of a larger care foundation which shares practices, it would be beneficial to evaluate the developed systems in a multitude of different nursing homes. Furthermore, the systems we created have only been deployed for relatively short periods of time (up to two months for CARE). As previous work has shown that the quality of user experiences changes significantly over time (Karapanos, 2013; Kujala, Roto, Väänänen-Vainio-Mattila, Karapanos, & Sinnelä, 2011), we intend to perform longer studies for a more thorough evaluation. During the deployment of CARE, we encountered problems with the Wi-Fi and sensor batteries, as well as other technical issues. These could impact user experience, since the analysis for the app was occasionally conducted with erroneous data. Therefore, the hardware infrastructure has a few flaws that require additional work before commercialisation.

Sometimes, the sensors positioned in the bed would stick to the bedsheets and end up in the washing machine. In addition, although the way we attached the sensors to patients was adequate, we could make them even less visible. We also experienced poor Wi-Fi performance with the automation units used to sync data to the cloud, and we therefore decided to update the summaries once a day, in the morning. Many of the aforementioned issues were detected with our monitoring system, which allowed us to take action quickly. With better equipment, we could consider increasing the script execution frequency to provide a more real-time monitoring system for nurses. However, a system with notifications and reminders might change the way nurses perceive the system’s usability. For example, if the nurses were required to check the system constantly, their workflow might suffer.

Considering the MNIRS solution, we evaluated its performance for 20 pharmaceuticals. While in the future we could build hyperlocal scan libraries for each patient, it would also be valuable to explore performance for more extensive training sets as well as opportunities for crowdsourcing (Hosio, Goncalves, van Berkel, & Klakegg, 2016; Hosio et al., 2017; Luo, & Kuutila, 2016). We would also need to test MNIRS in a longer study to explore user adaptation and ensure that the system delivers high accuracy outside controlled experimental settings. Misclassifications could be dangerous and even life-threatening to patients. Furthermore, the MNIRS app could be integrated with patient lists and prescription systems to build more advanced functionality. In addition, we recognise that the sample holder has room for improvement, since most misclassifications in our
evaluation were caused by inadequate sample positions. A more advanced pharmaceutical holder which can automatically adjust the sample holder walls depending on object size and placement would solve this issue. This could be achieved by involving industrial designers with a higher level of expertise in design and 3D printing.

Overall, we believe the proposed systems represent significant contributions in the scope of mobile health technologies for nursing homes. While the CARE system may not increase efficiency, it has the ability to facilitate an increase in nurses' awareness of patients and their needs. Similarly, although the MNIRS solution may not entirely eliminate medication errors, it can nonetheless serve as a valuable tool for nurses when they are required to rapidly and accurately identify pharmaceuticals in-situ.
5 Conclusion

This thesis explored the use of assistive in-situ technology for caregivers (we focused on formal caregivers in this work) in nursing homes, and focus was placed on two topics within this scope, namely improving context awareness and medication management. The first topic was addressed by designing, building and implementing a sensor infrastructure combined with an app for caregivers in a nursing home. This system, which we named CARE, quantifies patients’ behaviour, analyses the data and informs nurses with valuable insights. The results of a two-month deployment in a local nursing home indicated that via CARE, nurses became more aware of patients’ needs. We addressed the second topic by combining a new generation of MNIRS devices with a custom-designed non-expert assistance tool (i.e., a casing with a sample holder and an Android app). As our solution was intended to enable non-experts to use MNIRS, we evaluated its performance for pharmaceutical identification when used by caregivers in nursing homes. The nurses could easily scan tablets with the app, which handled all the data processing and returned highly accurate classifications. This method significantly outperformed the current tools available in the nursing home, thereby indicating that our MNIRS solution could reduce medication mismanagement.

Throughout the thesis, we analysed and discussed the two systems (i.e., CARE and non-expert MNIRS for nurses) in detail and reported the evaluation results from multiple studies. By working closely with nurses, we created solutions that added value to their work and were integrated within their workflow. That said, the work conducted in this thesis represents but the first step towards improving these two systems in order to reach adequate performance for commercialisation. We are currently collaborating with industry partners to commoditise and commercialise both systems. As demands related to the aging population reach a critical level, assistive tools will become increasingly necessary for enhancing care quality. With the rapid innovation and development of hardware, technological interventions such as these will also become increasingly prevalent in nursing homes. Yet, we must emphasise that although such technology can complement the excellent work carried out by caregivers, it will never fully replace it.
List of references


Original publications


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*Original publications are not included in the electronic version of the dissertation.*


683. Tomperi, Jani (2018) Predicting the treated wastewater quality utilizing optical monitoring of the activated sludge process

684. Fazel Modares, Nasim (2018) The role of climate and land use change in Lake Urmia desiccation


687. Hildebrandt, Nils Christoph (2018) Paper-based composites via the partial dissolution route with NaOH/urea


690. Niva, Laura (2018) Self-optimizing control of oxy-combustion in circulating fluidized bed boilers

691. Alavesa, Paula (2018) Playful appropriations of hybrid space: combining virtual and physical environments in urban pervasive games

692. Sethi, Jatin (2018) Cellulose nanopapers with improved preparation time, mechanical properties, and water resistance


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