Assessment of the implementation of optical artificial intelligent sensors for night-time care delivery in a long-term care setting

Thesis

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Summary

Background: Life expectancy is growing, and, with it, the number of elderly is growing as well. The pressure on delivering high-quality, labour-intensive long-term healthcare is rising because of this increasing elderly population. The use of artificial intelligence (A.I.) systems can potentially improve the effective allocation of healthcare professionals. However, the costs of technological innovations are high. Moreover, clients may be resistant to these technologies, and these innovations must improve their capabilities before wider implementation. In addition, healthcare professionals, such as nurses, are worried to lose their jobs because of A.I. technology.

Purpose: To gain insight into the experience of healthcare professionals in the implementation and adoption of optical A.I. sensors for night-time care delivery in long-term elderly care.

Methodology: The use of optical A.I. sensors in a long-term elderly care setting was evaluated using the non-adoption, abandonment, scale-up, spread, and sustainability framework. The qualitative analysis entailed eleven semi-structured interviews with (night-time) healthcare professionals.

Findings: The optical A.I. sensors were found to be beneficial for the quality of sleep and clients with dementia in long-term care maintain their own control of their night-time. These clients were not aware that they could call a nurse when they needed help. Nowadays, fewer regular checks are carried out, which interrupted the clients' sleep fewer. The optical A.I. sensors would activate nurses when an abnormal movement occurred in the client's room. What the optical A.I. sensors saw as normal and abnormal movements was customised per client. The data shows that the use of optical A.I. sensors increases the clients' safety and quality of sleep. In addition, the night-time nurses could provide care more efficiently, which resulted in more free time for the clients. However, the optical A.I. sensors need to be developed even further to increase the embedding and adaptation over time.

Practical Implications: Overall, the experience that healthcare professionals have with the optical A.I. sensors was positive. However, introducing and implementing optical A.I. sensors remains difficult. Healthcare professionals are more likely to implement and adopt to new technology if it has benefits for the clients. The adopter system needs to experience the optical A.I. sensors first before it can adopt new work routines.

Samenvatting

Achtergrond: De levensverwachting neemt toe, en daarmee ook het aantal ouderen. De druk op het leveren van hoogwaardige arbeidsintensieve langdurige gezondheidszorg neemt toe door deze toenemende ouderenpopulatie. Het gebruik van kunstmatige intelligente (A.I.) systemen kan de effectieve inzet van zorgprofessionals verbeteren. De kosten van technologische innovaties zijn echter hoog, patiënten kunnen zich tegen deze technologieën verzetten en deze innovaties moeten hun mogelijkheden verbeteren alvorens de innovatie op grotere schaal kan worden toegepast. Bovendien bestaat er onder zorgverleners, zoals verpleegkundigen, onzekerheid over het verlies van hun baan als gevolg van A.I. technologie.

Doel: Inzicht verkrijgen in de ervaringen van zorgprofessionals bij de implementatie en adoptie van optische A.I. sensoren voor nachtzorg in de langdurige ouderenzorg.

Methodologie: De evaluatie van optische A.I. sensoren in een langdurige ouderenzorg setting is geëvalueerd aan de hand van het "non-adoption, abandonment, scale-up, spread, and sustainability framework". De kwalitatieve analyse omvatte elf semigestructureerde interviews met (nacht) zorgprofessionals.

Bevindingen: De optische A.I. sensoren verbeterende de kwaliteit van slapen en cliënten met dementie in de langdurige zorg behouden hun eigen regio over de nachtzorg. De cliënten met dementie waren zich er niet van bewust dat ze een verpleegkundige konden bellen als ze extra hulp nodig hadden. Tegenwoordig worden er minder regelmatige controles uitgevoerd, waardoor de nachtrust van de cliënten minder werd onderbroken. De optische A.I. sensor activeerde verpleegkundigen wanneer er een abnormale beweging had plaatsgevonden in de kamer van de cliënt. Wat de optische A.I. sensoren zagen als een normale en abnormale beweging werd per cliënt aangepast. De data liet zien dat het gebruik van optische A.I. sensoren de veiligheid en de kwaliteit van de slapen van de cliënten verhoogden. Daarnaast konden de nachtverpleegkundigen efficiëntere zorg verlenen, wat resulteerde in meer tijd voor de cliënten. De optische A.I. sensoren moeten zich echter nog verder ontwikkelen om de inbedding en aanpassing over een langere periode te vergroten.

Implicaties voor de praktijk: Over het algemeen was de ervaring die zorgprofessionals hebben met de optische A.I. sensoren positief. Echter, het introduceren en implementeren van optische A.I. sensoren blijft moeilijk. Professionals in de gezondheidszorg zijn eerder geneigd nieuwe technologie te implementeren en te adopteren als het voordelen heeft voor de cliënten. Het adopter systeem moet eerst ervaring opdoen met de optische A.I. sensoren voordat het nieuwe werkroutines kan adopteren.

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Chapter 1. Introduction

This chapter starts with the problem analysis of this study. It provides insight into the implementation of technology in healthcare. Next, the aim and research question is defined. The social and scientific relevance is explicitly explained afterwards. The last part of this chapter contains a brief reading guide.

1.1 Problem Analysis

Life expectancy is growing, and, with it, the amount of elderly is growing as well (Garssen, 2011). In 2018, 3.2 million people reached the age of 65 and above in the Netherlands (Rijksinstituut voor Volksgezondheid en Milieu, z.d.). In the Netherlands, 4.5% people are 80 years and older (Centraal Bureau voor de Statistiek, 2020). Thus, the pressure on delivering high-quality, labour-intensive long-term healthcare is rising because of this increasing elderly population (Garssen, 2011).

In the Netherlands, the Ministry of Health, Welfare, and Sport is focusing on e-health to improve the quality and safety of healthcare (Meijnckens, 2016). E-health is “an emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the internet and related technologies” (Eysenbach, 2001, p. 2). The use of artificial intelligence (A.I.) systems can improve the effective allocation of healthcare professionals (Meijnckens, 2016).

A.I. systems can provide real-time information about the status and behaviour of clients and require less human interference (Jiang et al., 2017). A.I. has been referred to as “systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals” (Guarda, 2019, p. 361). An example of an A.I. system is the optical sensors. These “computer eye” sensors can observe motions through algorithms and provide nurses with relevant information to help them decide whether action is necessary, which is especially helpful in situations in which a limited number of “human eyes” are available. Delivering high-quality care during night shifts is a specific issue when professionals have to deliver the care mostly alone (Pueyo, Toupin, & Volkoff, 2011). Technology can help with staff shortages (Meijnckens, 2016).

The growing number of elderly with dementia is one of the main reasons to develop technologies that are beneficial for people with dementia (Astell et al., 2019). The positive benefits of technology for people with dementia may include empowering them with their activities of daily living (ADLs) and leisure (Astell et al., 2019). Developing new technologies is necessary for risk reduction and prevention in the near future. In addition, technology adds value to well-being, health, and healthcare (Pieterse, Kip, & Cruz-Martines, 2018). Nurses already try to improve the well-being, peace, and safety of clients during the night (Fąfara et al., 2016). Nurses checking on clients during the night may disturb the clients' sleep. Sleep disturbance has different consequences for long-term care clients. It results in tiredness during the day and having more trouble falling asleep (Irwin & Vitiello, 2019). Studies have shown that clients prefer less privacy due to A.I. technology in their rooms to regular checks during the night (Vandenberg et al., 2017). It does, however, potentially conflict with the intention to humanly control and check every client during the night, and the experiences of healthcare professionals with A.I. technology are unknown.

However, there are certain known barriers to implementing technology in the healthcare sector (Greenhalgh et al., 2018). The costs of technological innovations are high, and clients may be resistant to these technologies. Moreover, these innovations may not be in line with the legal system (Greenhalgh et al., 2018; Otto & Harst, 2019). Legal frameworks that include responsibility are often missing, which makes the implementation of A.I. technology harder (Otto & Harst, 2019). The high costs occur due to a lack of funding. In addition, proof of cost-effectiveness is lacking too (Otto & Harst, 2019). Healthcare professionals who are trained according to well-defined and high-level standards may potentially be afraid to lose their jobs because of A.I. systems (Meijnckens, 2016; Van Gorp & Mulder, 2018). In addition, healthcare professionals can have negative associations with technology in general (Otto & Harst, 2019). Technology may also negatively influence the communication between clients and their healthcare professionals (Otto & Harst, 2019). Resistance to change and bad attitudes toward technology are not the only reasons not to implement technology; complex psychological factors can also have their influence on the failure of implementing a technology (Cobelli, Cassia, & Burro, 2021). The lack of integration of technology in the healthcare sector is an additional implementation challenge (Otto & Harst, 2019).

Due to a lack of evidence about technology's impact on the healthcare sector, the potential benefits of technology are hard to see or were not reached, resulting in non-adoption of technology (Pieterse et al., 2018; Otto & Harst, 2019). The friction between technology and healthcare results in different challenges during the implementation of new technology (Grisot, Vassilakopoulou, & Aanestad, 2018). In particular, the perspective of healthcare professionals is lacking in evaluations (Pieterse et al., 2018). It is not known what influence these barriers and challenges have on the implementation of A.I. systems, but it is known that the current uptake of e-health, despite its potential, in long-term care is limited (Van Gorp & Mulder, 2018). Therefore, this study provides insight into the implementation and adoption of A.I. technology from the perspective of (night-time) healthcare professionals in long-term care.

1.2 Aim and Research Question

This research aims to assess healthcare professionals' experiences with optical A.I. sensors. By analysing the implementation and adoption of optical A.I. sensor technology, improvements for further implementation can become visible. The main research question is as follows:

"What are the experiences of healthcare professionals with the implementation of optical A.I. sensor technology for night-time care delivery in a long-term care setting?"

1.3 Reading Guide

The next chapter contains the theoretical framework. This theoretical framework provides further insight into the different domains of the non-adoption, abandonment, scale-up, spread, and sustainability (NASSS) framework of Greenhalgh, et al. (2017), and it elaborates on the context of the implementation of technology in long-term night care. Then, the methods used in this study are explained, and the context of the study is further elaborated. In Chapter 4, the results of the study are presented. Finally, Chapter 5 contains the discussion and conclusion. The limitations, implications, and further research are discussed in this last chapter. In addition, the answer to the main question can be found in Chapter 5 as well.

Chapter 2. Theoretical Framework

Several theoretical models for the adoption of technologies have been developed (Hulter et al., 2020). The technology acceptance model is about the motivation of the users. This model does not cover the acceptance of the technology by the organisation (Pieterse et al., 2018). Another framework, the DOI (diffusion of innovations), identifies different characteristics of the technology. Moreover, the organisational context is not included in this framework (Pieterse et al., 2018). NASSS framework of Greenhalgh et al. (2017) includes, among others, the organisational context. However, the value proposition is an important factor of the framework too (Pieterse et al., 2018). So far, no points of critique are found for this model (Hulter et al., 2020). This study needs a broad framework because of the different barriers in different domains that are present in the implementation of technology. However, the NASSS framework is not complete. It cannot be used for making strong predictions about missing elements, nor can it provide simple answers to complex problems with the implementation and adoption of technology (Greenhalgh et al, 2017).

The NASSS Framework

The implementation of technological healthcare innovations faces many barriers, for example, technological barriers, clients or staff barriers and barriers in finance, which lead to non-adoption (Greenhalgh, et al., 2017). Greenhalgh et al. (2017) created the NASSS framework for implementing, spreading, designing, and sustaining long-term technological innovations. The more complex an intervention is, the less likely it is to be adopted (Greenhalgh et al., 2017). Another reason is the lack of support of healthcare

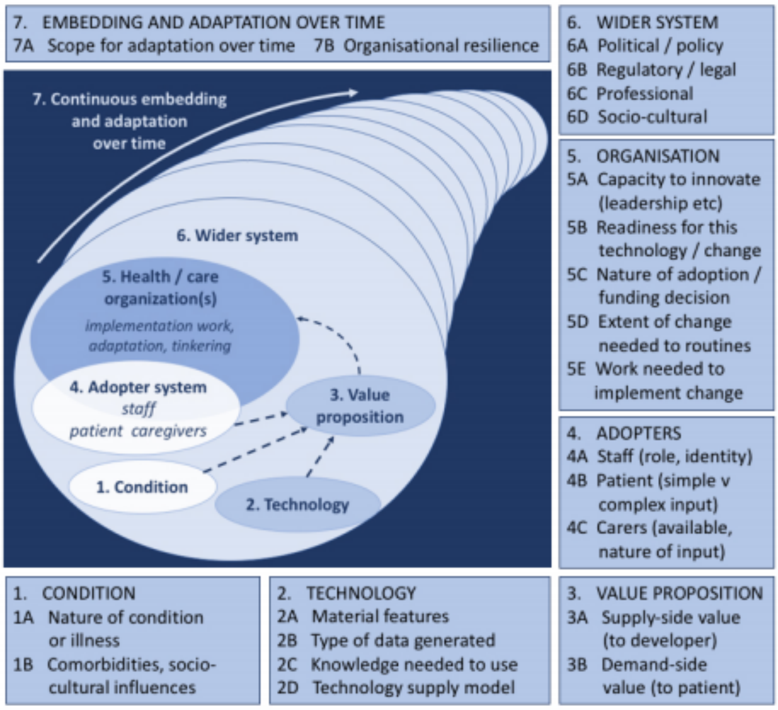

Figure 1 NASSS framework (Greenhalgh, et al., 2017)

professionals, which also results in non-adoption (Wade, Eliott, & Hiller, 2014). The resistance of healthcare professionals can be categorised into four topics of resistance: (1) policy, (2) socio-material limitations (e.g., reliability), (3) changing practice, and (4) changing relationships (Greenhalgh et al., 2017).

The NASSS framework (Figure 1, Annex II) addresses seven interacting domains. The five topics of the NASSS framework - non-adoption, abandonment, scale-up, spread, and sustainability - are covered within seven domains (Greenhalgh, et al., 2017). The seven domains (see Figure 1) can be characterised by the following terms: “simple”, “complicated”, or “complex” (Greenhalgh & Abimbola, 2019). If most of the domains are categorised as simple, the technology is likely to be implemented and spread (Greenhalgh & Abimbola, 2019); however, this is not likely to happen. If the domains are mostly characterised as complicated, the technology might be implemented, but it will take more time and budget (Greenhalgh & Abimbola, 2019). Additionally, implementing a technology when most of the domains are complex is rarely successful (Greenhalgh & Abimbola, 2019). Greenhalgh and Abimbola (2019) have advised learning to deal with complexity rather than eliminating it. There is an interaction between the domains in a simple or complicated system. This interaction results in the predictability of the system (Greenhalgh et al., 2018). In a complex system, these domains interact unexpectedly, which makes the adoption harder (Greenhalgh et al., 2018).

The NASSS framework can be used to structure conversations and ideas, identify innovations with less chance of adoption, and identify challenges in implementation on the micro, meso, and macro levels (Greenhalgh et al., 2017). The NASSS framework can also be used to implement and scale up innovations and learn from implementation errors (Greenhalgh et al., 2017).

2.1 Condition

The domain “condition” can be categorised as simple, complicated, or complex (Greenhalgh et al., 2018). A simple condition has clear boundaries, can be predicted, and is clearly understood. A complex condition, in contrast to a simple condition, has more complicated logistics (Greenhalgh et al., 2018). Greenhalgh et al. (2018) categorised dementia as a complex condition. This categorisation is made because there are no clear boundaries and dementia is unpredictable, faced by comorbidities, and influenced by socio-cultural factors. As a result, technology is even more necessary and useful (Greenhalgh et al., 2018). Surprisingly, non-adoption and abandonment of new technologies occur more often when the condition is complex (Greenhalgh et al., 2018).

Dementia is a worldwide problem, which already affects more than 250,000 people in the Netherlands alone (Van den Pol, 2020). Dementia is a brain disease that has a negative influence on cognitive abilities (Arvanitakis & Bennett, 2019). It is caused by another brain disease, such as Alzheimer's disease, or a medical condition somewhere else in the body (Arvanitakis & Bennett, 2019). It develops over the years. Symptoms of dementia are problems with short-term memory, anxiety, and avoiding social events (Arvanitakis & Bennett, 2019). The treatment for dementia differs from person to person and can only reduce the symptoms. The treatment is, for example, focused on preventing falls or preventing people from getting lost (Arvanitakis & Bennett, 2019). Balanced food and good sleep can decrease the symptoms of dementia (Arvanitakis & Bennett, 2019).

People with dementia have an increased chance to experience sleep disturbance (Webster, Powell, Costafreda & Livingston, 2020). Potentially, 40% of clients with dementia experience sleep disturbance (Webster et al., 2020). During the night, clients sleep only 56.7% of the time (Moyle et al., 2017). If clients are awake during the night, they are potentially more likely to fall asleep during the day (Webster et al., 2020). Consequently, their day-and-night rhythm might change. In addition, they are more likely to fall because of sleepiness (Webster et al., 2020).

Falling has a lot of negative consequences, such as morbidity and mortality (Dhargave & Sendhilkumar, 2016). The elderly in nursing homes have a higher risk of falling (Dhargave & Sendhilkumar, 2016). In addition, people who are diagnosed with dementia have a 66% higher chance to fall (Kröpelin, Neyens, Halfens, Kempen & Hamers, 2013). The risk of falling increases due to different indicators, such as balance problems, age, anxiety, disorientation, and gender (Dhargave & Sendhilkumar, 2016; Kröpelin et al., 2013; Meulenberg, Van Dijk, Van de Sande, & Habbema, 1991; Van Dijk, Meulenberg, Van de Sande, & Habbema, 1993).

There is some contradiction found in the literature about the influence of personal characteristics on the risk of falling. For example, Dhargave and Sendhilkumar (2016) and Meulenberg et al. (1991) found that women are more likely to fall, whereas the study of van Dijk et al. (1993) showed that men have twice as much risk to fall. Due to the influence of personal characteristics, A.I. technology must be customised according to every person's needs. In addition, 5% of the falls happen during the night (Dhargave & Sendhilkumar, 2016). Therefore, although this is a small percentage, technology that detects falls at night can be valuable. Since people with dementia are in less control at night, they may fall and lie on the floor for long periods, with all the consequences such a situation entails (Dhargave & Sendhilkumar, 2016).

There are different technologies for dementia support (Hall, Wilson, Stanmore, & Todd, 2019). The so-called devices used "on" people with dementia (e.g., for monitoring movement and activity) are preferred by long-term care organisations. These devices can increase safety and potentially help to alarm healthcare professionals when the client cannot alarm the healthcare professionals by themselves anymore (Hall et al., 2019).

2.2 Technology

The second domain is about technology. The complexity level of the domain "technology" is based on use, the type of data being collected, intellectual features, and the supply chain (Greenhalgh et al., 2018). The complexity is measured by its changeability, predictability, contestability, and relation with its changing environment (Greenhalgh et al., 2018). This domain is categorised as simple if the technology is freestanding, can transparently measure the condition, requires simple training, and is generic (Greenhalgh et al., 2017).

The healthcare sector already has a lot of data, which makes it a promising sector for the application of A.I. systems (Gaube et al., 2021). The systematic review of Kruse, Fohn, Umunnakwe, Patel and Patel (2020) indicates potential facilitators, barriers, and medical outcomes of technological innovations. Technological innovations might improve cognitive abilities and medical outcomes, and they might increase ADLs and autonomy (Kruse et al., 2020). In contrast, Gaube et al. (2021) found that the few studied cases of the implementation of A.I. systems did not show improved medical outcomes. To increase the safety of healthcare provision, it is important to reduce abnormal activities, such as falling (Mabrouk & Zagrouba, 2018; Ren & Peng, 2019). There is an increasing demand for a system that can identify motion and alarm healthcare professionals directly (Mabrouk & Zagrouba, 2018).

Optical A.I. sensors are developed to monitor human movements and, for example, prevent falls in long-term care (Neves & Vetere, 2019) and are based on an algorithm (Bourke & Lyons, 2008). This algorithm can detect motion and differentiate falls from ADLs. If a client falls on the ground, the angular acceleration, angular speed, and body angle are different than they are while performing ADLs (Bourke & Lyons, 2008). The night-time nurse may receive a message on the phone when the A.I. technology detects motion (Vandenberg et al., 2017).

There are three types of fall- or motion-detection systems: (1) deployed sensors, (2) ambient sensors, and (3) vision-based sensors (Ren & Peng, 2019). Optical sensors are vision-based sensors. Vision-based sensors can detect motion by monitoring the body shape (Mabrouk & Zagrouba, 2018). The optical sensors make use of deep learning. They are self-learning, and, thus, the training data is important (Mabrouk & Zagrouba, 2018). In addition, the system cannot learn all types of motions and abnormal activities. Therefore, the sensors make use of algorithms. The study of Ren and Peng (2019) showed the importance of testing these algorithms in real life. There was a significant difference between the systems using testing data and those using real-life data.

The study by Aziz, Musngi, Park, Mori, and Robinovitch (2017) compared five accelerometer-based algorithms that used threshold-based methods and five systems that used the self-learning method. The self-learning systems had better motion detection (Aziz et al., 2017). Bourke et al. (2010) concluded that an algorithm for a motion-detection system should include the impact, posture, and velocity. With these three components, the systems can reach complete sensitivity (Bourke et al., 2010). An accelerometer in vision-based motion-detection systems is necessary for the detection of falls and best performance (Bourke et al., 2010).

Different types of cameras can be used for vision-based motion-detection systems. The first is the single red green blue (RGB) camera (Ren & Peng, 2019). These cameras make use of the body shape, the detection of inactivity, and the motion of clients to detect falls. Multiple RGB cameras make use of more than one camera. The calibration of the camera is important but takes a lot of time (Ren & Peng, 2019). The last type of camera is the depth camera. The depth camera can detect motion and falls by analysing the body shape and the distance between a person's head and the floor (Ren & Peng, 2019).

2.3 Value Proposition

"Value proposition" is the third domain of the NASSS framework. The value proposition contains both the supply-side value and the demand-side value. The supply-side value focuses on the business case of the developer of the new technology (Greenhalgh et al., 2017). The demand-side value is determined by the safety, efficacy, desirability, and cost-effectiveness of the innovation (Greenhalgh et al., 2017). This domain is categorised as simple if these aspects are present. If there is a significant possibility that these aspects will not be achieved, the domain is complex (Greenhalgh & Abimbola, 2019).

Healthcare professionals and A.I. technologies need to work together to improve the access to care, cost-effectiveness, and care effectiveness, such as quality, safety, and efficiency (Chen & Decary, 2020). Shaw, Fudzicz, Jamieson, and Goldfarb (2019) defined different potential values for implementing A.I. innovations for different healthcare stakeholders. An A.I. innovation might add value for healthcare professionals if it is a helpful decision-support system (Shaw et al., 2019). The data should be visualised clearly through a communication tool. A clear communication tool might improve whether and how the data of the technology is used (Shaw et al., 2019). The elderly are more willing to adopt an A.I. technology if the desired outcomes can be achieved (Changizi & Kaveh, 2017). Achieving the desired outcomes may outweigh the negative consequences of A.I. technology, for example, the risk of loss of privacy (Tran, Riveras, & Ravaud, 2019). The security of data and, with it, the privacy of clients might be necessary to add value to the technology. Cloud-based analytics is an option to ensure data safety (Shaw et al., 2019). However, the consequences of using clients' data should be evaluated (Chen & Decary, 2020). In addition, implementing an A.I. technology is complex and costly. The innovation should be cost-effective for healthcare organisations (Chen & Decary, 2020). Shaw et al. (2019) concluded that all stakeholders need to support the implementation of the new technology to ensure that value is added for the demand and support sides.

2.4 Adopter System

The challenge faced by the fourth domain, "the adopter system", of the NASSS framework is about the changing identity of the adopter (Greenhalgh et al., 2018). If the adopter system does not need to change its practices or identities, this domain is categorised as simple. If the technology is a threat to the identity and values of the adopter system, it is categorised as complex (Greenhalgh et al., 2018). However, some healthcare professionals might be afraid to lose their jobs. In addition, the judgements of the adopter system are difficult and unpredictable to deal with (Greenhalgh et al., 2018). A gap between adopters can arise when there is a group of innovators on the one hand and a group of healthcare professionals who are reluctant to embrace the new technological innovation on the other. This gap makes the adoption and scale-up of a technology harder (Greenhalgh et al., 2018). The domain adopter system also contains the patient and their informal caregiver (Greenhalgh et al., 2017). The complexity of these aspects is about what the implementation of the technology is expecting of them. However, the focus of this study is on healthcare professionals.

Night-time nurses try to deliver care as comfortably and quietly as possible to improve clients' sleep (Gustafsson, Asp, & Fagerberg, 2009). Nevertheless, night-time nurses need to conduct treatments (e.g., switch positions of clients) during the night. Preparing the care for the day is an additional task the night-time nurses often need to do (Gustafsson et al., 2009). Compared to the US, the Netherlands has a lower nurse-to-client ratio during the night (Vandenberg et al., 2017). In the Netherlands, one nurse takes care of an average of 36 clients with dementia during the night (Vandenberg et al., 2017). In contrast, in the US, one night-time nurse takes care of only 15 clients. In 2014, the nursing homes in the Netherlands reported a shortage of 53% in nursing staff (Van der Meulen, 2019). Marć, Bartosiewicx, Burzyńska, Chmiel, and Januszewicz (2019) have claimed that the shortage of nursing staff has reached a critical level.

Night Care

The article of Fąfara et al. (2016) stated that night-time nurses experience a shortage of night labour force as one of the biggest problems during the night. The labour force issues can result in high work pressure with negative influences on the nurses (Van der Meulen, 2019). A.I. technology can improve the work process of the nurses (Van der Meulen, 2019), and it can provide extra safety for the clients. It activates the nurses when a client might be in trouble, decreasing the number of checks the nurses would have done otherwise. Nurses can spend their time differently because of the improved processes, which reduces the workload and improves the client–nurse relationship (Van der Meulen, 2019). However, night-time nurses might need to adopt a new task routine.

Improving the work process also has positive effects on the clients in long-term care (domain "condition"). With optical A.I. sensors, nurses do not need to go into the private room of the client to check on them, which improves the client's quality of sleep (Irwin & Vitiello, 2019). If a client is disturbed during their sleep, it takes them longer to fall asleep again. Every time a client's sleep is disturbed, the time before they fall asleep again increases (Irwin &

Vitiello, 2019). Furthermore, with a good quality of sleep, clients will have more energy to stay awake during the day (Irwin & Vitiello, 2019).

Optical A.I. sensors are an example of the so-called “on” technologies (Hall et al., 2019). They signal when a client needs extra support; thus, nurses can provide potentially more relevant and on-time care, which increases patient-centredness (Hall et al., 2019). Hall et al. (2019) explained that nurses might experience the “on” technologies as a non-supportive tool. Nurses pointed out that “on” technologies feel like a “Big Brother” tool. Nurses feel that their activities can be measured, even when doing so is impossible (Hall et al., 2019). This position remained intact, even after the management explained that this was not the case (Hall et al., 2019). Hall et al. (2019) questioned if this “on” technology is preferable and if it influences the open culture of an organisation.

Staff

Introducing a new technology might raise different emotions among healthcare professionals (Engström, Lindqvist, Ljunggren, & Carlsson, 2009). On the one hand, healthcare professionals can be concerned about the workload and losing control over the care, question the relevance of the technology, and potentially be afraid to be less able to deliver patient-centred care (Engström et al., 2009). The adopter system might need to adopt some new roles to work with technology. In addition, the technology might not be suited for every condition or client. On the other hand, healthcare professionals can see technology as a positive and necessary change (Engström et al., 2009). A lack of knowledge about the technology might raise different made-up scenarios. Engström et al. (2009) studied the implementation of technology in a long-term care setting for dementia. They interviewed 14 healthcare professionals before, during, and after the implementation of different technologies. After the implementation, healthcare professionals wanted the organisation to implement more technology (Engström et al., 2009). They made an improvement in delivering healthcare as well as in their job satisfaction. Although some technologies do not fit every client, most of the clients experienced positive effects, such as increased security and freedom (Engström et al., 2009). Engström et al. (2009) concluded that healthcare professionals are concerned about new technologies in the beginning, but the technologies can increase their job satisfaction and improve patient-centred care. Healthcare professionals need time to be familiarised with the new technology during the implementation (Engström et al., 2009).

Not only are healthcare professionals concerned about new technologies (Engström et al., 2009), but they are also sceptic about it (Gaube et al., 2021). Gaube et al. (2021) stated that A.I. systems can be beneficial only if healthcare professionals can balance scepticism and trust in new technologies. The balance between scepticism and trust is important. On the one hand, if healthcare professionals do not trust the A.I. system, the system is not used (Gaube et al., 2021). On the other hand, too much trust in A.I. systems can result in negative medical outcomes (Gaube et al., 2021). Godoe and Johansen (2012) found that optimism and willingness to innovate have a positive influence on the perceived experience of technology. The usefulness and ease of use are experienced more easily (Godoe & Johansen, 2012). In addition, experienced usefulness stimulates the usage of technology. Gaube et al. (2021) concluded that evaluating the consequences of implementing A.I. systems can be hard because of the differences between healthcare professionals' insight and their behaviour. In addition, healthcare professionals experience difficulties in filtering inaccurate advice (Gaube et al.,2021). As a result, healthcare professionals may not rely solely on technology for advice and need to consult a colleague for their advice. Thus, there is tension between human intelligence and A.I. A.I. systems need to be further developed to create a more optimal collaboration (Gaube et al., 2021) so that healthcare professionals can rely on A.I. systems more often.

2.5 Organisation

The fifth domain, "organisation", is about the adaptability of the healthcare organisation (Greenhalgh et al., 2017). The complexity in this domain arises from the capacity of the organisation to innovate, the readiness, the quality of adoption, the number of necessary changing work routines, and the amount of necessary work to implement the A.I. technology (Greenhalgh & Abimbola, 2019). Leaders who are willing to make an impact across the organisation by providing necessary resources might improve the implementation of A.I. technology (Chen & Decary, 2020). Not only a leader, and their team, who is willing to implement A.I. technology is necessary, but an open culture in the organisation also improves the implementation of A.I. technology (Chen & Decary, 2020). In addition, the collaboration between healthcare organisations and other sectors can be beneficial to improve the implementation of A.I. technology in the healthcare sector (Chen & Decary, 2020).

The capacity of the organisation to innovate is important to determine the uptake of technology (Wozney et al., 2017). Work routines that do not require much adjustment might accelerate implementation. Nevertheless, technologies often require major adjustments from the organisation and individual healthcare professionals (Wozney et al., 2017). Knowledge about new technology, the way it can be used, and additional safety is potentially necessary for healthcare professionals in the organisation to adopt new work routines (Kip, Oberschmidt, & Bierbooms, 2020; Wozney et al., 2020). Nevertheless, healthcare professionals should get enough time to adopt their work routines. The organisation should think about how it can overcome the gap between the early adopters and the non-adopters in the organisation (Wozney et al., 2017).

The digital infrastructure of the organisation often contains different applications that are not well connected (Wozney et al., 2017). The digital infrastructure that needs to connect these applications is lacking. The lack of a digital infrastructure can increase the amount of work necessary to implement the new A.I. technology (Wozney et al., 2017). The better the digital infrastructure is, the less additional work is required (Kip et al., 2020). Therefore, collaboration between the healthcare sector and the digital industry is necessary to improve the digital infrastructure (Wozney et al., 2017). Nevertheless, this collaboration is uncoordinated. In addition, the ongoing costs of A.I. technology should be taken into account to make decisions about the funding. Obligatory cost-benefit analyses should make the costs easier to understand (Kip et al., 2020; Wozney et al., 2017).

2.6 Wider Context

The “wider context” is the sixth domain of the NASSS framework. The complexity of this domain is determined by the economic and regulatory requirements and the current policies about technology. Additionally, the social-cultural context is also a factor that determines the programme rollout (Greenhalgh et al., 2017). If the financial and regulatory requirements face many challenges and the stakeholders are not supportive, the domain is classified as complex. This domain is important to explain why a successful pilot will not automatically result in a wider scale-up, spread and sustainability (Greenhalgh et al., 2017).

In the Netherlands, a health technology assessment (HTA) is becoming increasingly important in deciding the use of technology in the healthcare sector (Wammes, Jeurissen, Westert, & Tanke, 2019) because a technology that is cost-effective in one setting may not automatically be cost-effective in another setting. It is a political choice when subsiding technology (Wammes et al., 2019). However, these subsidies might be necessary for the wider context to adopt the technology. Nevertheless, the privacy of clients and healthcare professionals needs to be protected through cybersecurity (Coventry & Branley, 2018), especially when clients and healthcare professionals experience technology as a "Big Brother" tool (Hall et al., 2019). The cybersecurity of the data of clients and healthcare professionals is considered to be central in new legislation and regulation of healthcare technology (Convertry & Branley, 2018). The current regulations are inadequately maintained (Parker et al., 2017). However, the type of technology and the risk of harm from the technology determine regulatory requirements. The legislation and regulations do not include accountability, truthfulness, and transparency. The government advises healthcare technology companies to protect these professional ethics (Parker et al., 2017). In this domain, it will be beneficial for the implementation of technology if stakeholders are supportive of technology (Greenhalgh et al., 2017). However, healthcare professionals might not be sufficiently included in decision-making processes (Mather, Cummings, & Gale, 2019); including healthcare professionals is potentially important in enabling other stakeholders to become proficient. Nevertheless, there are organisations that outline the expectations of all stakeholders for implementing and adopting new technology (Mather et al., 2019). This outline can potentially further involve stakeholders in decision-making processes.

2.7 Embedding and Adaptation Over Time

The last domain of the NASSS framework is "embedding and adaptation over time". The degree of complexity of this domain is determined by two aspects. The first aspect is about the number of barriers in adapting to and coevolving with the innovation over time (Greenhalgh et al., 2017). The way the organisation deals with unexpected developments is the second aspect (Greenhalgh et al., 2017).

The embedding and adaptation of healthcare technology over time can potentially be assessed by different factors, such as technology acceptance, efficiency, education, competency, communication, management, and policy (Yen, McAlearney, Sieck, Hefner, & Huerta, 2017). Nevertheless, the embedding and adaptation among older people will probably be harder (Fox & Connolly, 2018). In addition, privacy concerns may result in even less embedding and adaptation over time (Fox & Connelly, 2018). Yen et al. (2017) stated that more research on the process of embedding and adapting healthcare technology over time is necessary to improve the implementation of technology in this sector.

In summary, implementing a new technology requires reducing the complexity of all domains of the NASSS framework (Greenhalgh et al., 2018). The relationship between the different domains makes implementing technology complex. In this study, all domains of the NASSS framework are discussed.

Chapter 3. Research Methods

This chapter provides insight into the research process. First, the context of this research is explained. Second, the study design is clarified. Third, an overview of data collection is provided. Fourth, the data analysis is elaborated on, and, finally, the validity, reliability, and generalisability are taken into account.

3.1 Context

In the Netherlands, most of the elderly live in the provinces of South-Limburg, Groningen, and Zeeland (Kooiman, 2016). In Zeeland, 6.3% of the population is 80 years and older (CBS, 2020). The growing number of elderly in Zeeland increases the demand for care. Another demographic change that increases the pressure on the healthcare labour force is the fact that young adults move to big cities, such as Amsterdam, Rotterdam, and Utrecht (Kint & Kutterink, 2017). Only one out of four adults move back to Zeeland within three years (Kint & Kutterink, 2017). With the growing population of elderly in Zeeland and the outflow of young working adults, the pressure on the job market is rising.

This study took place in the organisation “Stichting Voor Regionale Zorgverlening” (SVRZ). SVRZ is a long-term healthcare organisation for the elderly in Zeeland. Hiring new (night-time) nurses is getting harder (Van der Meulen, 2019), and, to deal with this situation, technology might be helpful. SVRZ has implemented optical A.I. sensors in the residences of dementing clients at one location. The optical sensors are supposed to reduce the workload of healthcare professionals, especially during the night (Kepler Vision Technologies, 2020; Vandenberg, et al., 2017).

Kepler Vision Technologies is the developer of the optical A.I. sensors that the organisation uses. The developer has created algorithms for optical A.I. sensors. According to the developer, optical A.I. sensors reduce fake alerts from motion sensors (Kepler Vision Technologies, 2020).

3.2 Study Design

A qualitative study was conducted to answer the question *“What are the experiences of healthcare professionals with the implementation of optical A.I. sensor technology for night-time care delivery in a long-term care setting?”* The reason behind this choice is that the experiences of healthcare professionals are a central part of this study. The goal of the study was to gather the different experiences of healthcare professionals (Mortelmans, 2013). The data was collected in a real-life setting. This approach is called a field research approach (Mortelmans, 2013). A qualitative study can be used to get an in-depth understanding of a real-life setting (Yin, 2003). In addition, this method is used to understand the experiences of healthcare professionals instead of measuring them (Green, 2013). The researcher is influenced by her values and insights (Mortelmans, 2013). This study design allowed for a flexible method. In addition, triangulation was used. Interviewing was the main research method. A literature study was conducted to gain insight into known research and results (Mortelmans, 2013). In addition, meetings about optical A.I. sensors with the project group of SVRZ were attended.

3.2.1 Interviews

Interviews were used for answering the research question. The interviews were semi-structured. A topic list is the basis of a semi-structured interview (see Annex I; Mortelmans, 2013). The list contains subjects but no specific questions. The use of this topic list results in an open conversation with room to discuss other subjects, for example, one's experiences and opinions (Brinkman, 2000). The topic list is based on the NASSS framework from Greenhalgh et al. (2017).

The interviews took place mainly via video calling because of the ongoing COVID-19 pandemic. The interviews had a duration of 30–60 minutes each. The interviews took place with three managers of different locations, six night-time nurses, and two team leaders. The study consists of eleven interviews in total.

Clients with dementia were not interviewed. Due to their condition, their short-term memory is affected. This short-term memory is necessary for answering questions about their current sleep pattern. In addition, clients do not actively experience the optical A.I. sensors; the night-time nurses get an alarm from the sensor if the client performs an abnormal movement. Furthermore, the night-time nurses provide night care and know the most about the behaviour of their clients at night. For this reason, the choice was made to interview the night-time nurses instead of clients or their informal caregivers.

3.3 Data Collection

3.3.1 Approaching the Field

This thesis proposal was approved in March 2021. This period of time was the official start of the data collection process. The organisation was informed about the study in November 2020. The researcher is working at the organisation, which made it easier to contact certain persons. Internally, a project on optical A.I. sensors had been started. The researcher took part in the project group meetings to take notes and stay up to date with new developments. In addition, the researcher had contact with the developer of the optical A.I. sensors.

In March 2021, the first respondents were approached by their supervisors. The interviews took place through Microsoft Teams because of COVID-19. The same topic list was used for the respondents (Annex I). In addition, the researcher worked at the location with the optical A.I. sensors one night. During this night, the researcher experienced the night-time care delivery and the alarms triggered by the optical A.I. sensors.

3.3.2 Conducted Interviews

Eleven interviews were conducted by the end of the study. Three interviews took place with location managers. They are responsible for their respective location. Two interviews took place with team leaders and six with healthcare workers. The interviewees were anonymous. From here on, they are called respondents. Respondents were from different disciplines and had different values and insights, which made the group of respondents diverse and led to the collection of different opinions from different viewpoints.

Respondents of the location that did not adopt optical A.I. sensors were hard to recruit. They did not answer emails or were not open for interviews. Fortunately, the team leader and two night-time care nurses were interviewed from the location that did not adopt optical A.I. sensors.

3.3.3 Fieldnotes

The researcher attended seven meetings with the SVRZ project group, ten meetings with the developer, one meeting with the healthcare professionals of the location where optical A.I. sensors were delayed, and worked one night shift at the location with optical A.I. sensors. During the online meetings, notes were taken. Every meeting took place via Microsoft Teams.

The online meetings made it possible for the researcher to be less noticeable, which made it less likely that team members of the project group would provide biased answers.

During the night shift at the location with optical A.I. sensors, care delivery was observed. Clients' rooms were not entered to protect their privacy and because of the possibility that they could get interested or feel anxious when seeing an unknown person in the middle of the night. Notes were taken about the frequency of the alarms and the rounds the night-time nurse took during their shift.

3.4 Data Analysis

3.4.1 Coding

The data analysis of the eleven interviews is explained. The interviews were recorded after taking the permission of respondents. Most of the interviews had a duration of 40 minutes. All of the interviews were transcribed verbatim. The program Atlas.ti was used for coding the interviews. Respondents were Dutch, and, for this reason, the choice was made to conduct the interviews in Dutch. The interviews and observation reports were also coded in Dutch. The reason behind this choice was to avoid mistranslations that could lead to false interpretations (Suh et al., 2009).

The transcripts were coded abductively. Abductive coding is a combination of deductive and inductive codings. Deductive coding starts with certain predefined codes from the literature (Timmermans & Tavory, 2012). With these codes, the transcripts were analysed. Inductive coding analyses the transcripts and observation reports openly, meaning, without predefined codes. Codes are collected through analysing the transcripts (Timmermans & Tavory, 2012). Abductive coding sees the transcripts as new evidence about subjects that have already been studied (Timmermans & Tavory, 2012). A combination of predefined codes and open coding is the result of abductive coding.

The different domains of the NASSS framework were used as broader concepts to analyse the data. The different aspects of the domains are used as smaller concepts. In addition to these concepts, an open view was held to code inductively and analyse new concepts. First, three transcripts of different respondents with different healthcare functions were coded. These three transcripts provided a broad overview of the different important domains per healthcare professional. Most of the inductive codes were made during the coding of the first three transcripts. Afterwards, the remaining transcripts were coded randomly.

3.4.2 Ethical Consideration

Before each interview, respondents were asked for their informed consent. An informed consent document was not needed to be signed. It was made clear that the interviews would be anonymised and that their answers would not have formal consequences. In addition, it was explained that the data would be deleted upon completion of the research. An explanation about transcribing the interviews and the purpose of doing so were provided too. Some respondents asked to receive the transcript of their interview for their record. Some respondents explicitly asked to be informed about the results of the research. In addition, the research was explained before every interview officially started. Respondents had an insight into the research they were involved in. When the research was completed, the respondents who were interested received the results by email. In addition, SVRZ permitted the use of the name of the organisation in this study.

3.5 Validity, Reliability, and Generalisability

It is important to take validity and reliability into account. Validity refers to whether the results are specific and correct (Mortelmans, 2013). Validity is about finding the results that should be found and that correspond with the used methods (Mortelmans, 2013). The researcher should be as objective as possible, without regard to their values. Doing so was especially difficult for the researcher because of the dual role she had in the organisation; she had different interests as a master student and as a policy advisor for SVRZ. The topic list increases the validity (Annex I; Mortelmans, 2013). The validity of the results was maintained because the topic list was based on the literature. In addition, respondents worked at SVRZ, which made them reliable. Conclusions can be made on the different interviews (Mortelmans, 2013).

The reliability of the research was ensured by having the same researcher and methods throughout the research period (Mortelmans, 2013). It is impossible to conduct the same research in the same period or with a different researcher. The research took place at a specific setting in time, with specific social influences. The clear description of the methods of this study increases the reliability.

The research is partly generalisable. The research contains a case study of a long-term care organisation. The case study was performed over a relatively short duration. However, this research is applicable to other long-term care organisations or settings that provide dementia care (Mortelmans, 2013). In addition, it is especially applicable to organisations that face rising pressure in the job market. These organisations can learn from the implementation of optical A.I. sensors in this case study. Generalised results can be made when participants represent the research population (Mortelmans, 2013). Generalisability was guaranteed because participants differed from speciality and represented different groups in the organisation.

3.5.1 Triangulation

Due to triangulation, validity and reliability are increased. Triangulation means that different data sources are used (Mortelmans, 2013). In this research, interviews and a literature study were used as data sources. The different sources were used to find evidence; for example, when respondents experienced certain feelings, the literature was studied to see if these feelings were expressed more often. In addition, the different sources were also used for researching contradictory results.

Chapter 4. Results

This chapter presents the main results of the study of the implementation of optical A.I. sensors in the long-term care setting. The NASSS framework was used to analyse the organisation's case. Therefore, the seven domains of the NASSS framework were used.

4.1 Condition

Most clients with dementia are incapacitated. Data suggests that clients with dementia usually do not have the awareness that they can call a night-time nurse when they are in need. Optical A.I. sensors took over the alarm, which resulted in a direct alarm to the night-time nurse if, for example, a client had fallen. As can be seen in the data, the self-control of clients was increased by the use of optical A.I. sensors because it resulted in fewer regular checks by the night-time nurses. The optical A.I. sensors were customised; therefore, the night-time nurse was not notified if a client who could still easily walk was walking in their room. In addition, most clients who would come out of bed at night would go to bed all by themselves. They did not need the help of the night-time nurse to do this. This own control of clients decreased the feeling of control. The sensors alarmed a nurse only when someone had fallen or been out of bed for too long. Respondent 4 was surprised by the difference between the day and night shifts. Restless clients could walk around during the day. However, when after sunset, this was not an option for the nurses anymore. *"The nurses find that very difficult because in our standards and values, in our frame of reference, you don't walk around at 1 a.m.",* respondent 4 explained. Some psychogeriatric clients wandered during the night. "*They fiddle around in their room, go out into the hallway, or go into the room of their neighbour"*, respondent 1 said. Respondent 5 said that clients who walked around and got into the rooms of other clients were detected earlier by the optical A.I. sensors, thus increasing the ease at night.

4.2 Technology

The algorithm of the optical A.I. sensors is a self-learning algorithm, which means that the sensors learn the behaviour of the client and alarm the nurses if an abnormal movement occurs. The optical A.I. sensors were easy to use, and a short training was sufficient to know how to work with the sensors.

The optical A.I. sensors can be customised per client. During one of the meetings with the developer, it was explained that client X's alarm would be activated when they were 10 minutes out of bed, whereas client Y's alarm would be activated after they were 1 minute out of bed. "*We can adjust ourselves what the sensor sees as abnormal movements. For some clients, this will be sitting on the bed",* respondent 5 explained. What the optical A.I. sensors saw as a normal and an abnormal movement was customised per client. The night-time nurse received a notification on the phone when an abnormal movement occurred. The developer explained during one of the meetings that the notification included the room number of the client and the type of abnormal movement observed.

The optical A.I. sensors looked like a ball in the corner of the room; this observation was made while shadowing the night-time nurse. "They measured different points of the body, and no images were stored", respondent 3 explained. As a result, clients and night-time nurses could not be recognised. The sensors can be deployed during the night as well as the day.

"*The question is, how fast does the sensor adopt? How quickly does it know the client's pattern?"* respondent 4 asked herself. The developer explained that in the first period, the sensors had needed some time to learn the contours of clients and their behaviour. However, the optical A.I. sensors recognised contours and behaviour faster than they did earlier. "*The previous client was in the bed the other way around, so the sensor is giving a lot of error messages with the current client. It is a learning process. Now, the sensor has to learn the new behaviour of the client",* respondent 5 added as an example. Another example given by respondent 7 was about the learning process of the optical A.I. sensors when clients slept in their chairs instead of their beds.

When the optical A.I. sensors were installed, there was a short training. During one of the meetings, the training was explained. The developer explained what the sensors did and what the nurses needed to know about the sensors. Respondents 6, 7, 8, and 9 agreed independently of each other that in-depth training was not necessary. The nurses did not need to change any settings on the sensors. "*You just have to make sure that there are no curtains hanging in front of the sensor",* respondent 7 explained. The respondents 6, 7, 8, and 9 showed that experiencing the technology was an even more important aspect than the training itself. However, there were error messages from the optical A.I. sensors sometimes. Nevertheless, technical errors were passed on to the developer. However, there was one difficulty with the optical A.I. sensors in the morning: *"You can get a lot of notifications when people wake up early. Then there are additional bells from colleagues standing at the door. As a result, you may not get some [fall] notification of the sensors"*, respondent 6 explained.

4.3 Value Proposition

The data shows that optical A.I. sensors are desirable for taking over the regular checks by night-time nurses. Moreover, the clients' safety was increased because the night-time nurse was notified when an abnormal movement occurred in the room of the client. In summary, the night-time nurses were able to work more efficiently, which resulted in the cost-effective use of the sensors.

Furthermore, the data shows that the sensors improved the quality of sleep of clients due to less frequent checks by the night-time nurses. During one of the meetings, healthcare professionals explained that two regular checks per night are normal, whereas, previously, eight rounds were the standard. However, it is important to reduce the number of regular checks as much as possible with the help of the optical A.I. sensors to retain the sleep of the client. Respondent 3 emphasised that some clients would wake up easily when a nurse checked on them. Respondent 8 noticed *"Some clients have great difficulty falling asleep again. I do notice that clients sleep better [with fewer regular checks]".* Data further shows that less frequent checks increase the period of sleep of clients. Respondent 2 said, *"I found the night shift very restless. And it was especially restless because of the different checks which were made. They [night-time nurses] checked all the rooms to see if clients were sleeping. I heard the nurse say when she opened the door: 'Stay asleep, I only came to see if you were all right'. Ten minutes later, a bell rang because that person needed to pee. When you are awake you have to pee. So, you have the turmoil. At the residences [of dementing clients], if clients have woken up you need some persuasion to convince them that it's still night".* Respondent 2 said that night-time nurses were aware the clients woke up during the regular night shifts. Nevertheless, respondent 6 explained that she checked every client even though some clients woke up. Respondent 6 added that she also checked clients when the optical A.I. sensors did not give any indication.

The safety of clients increased due to the optical A.I. sensors which decreased the time that clients needed to wait for help. In addition, clients noticed the quick attendance of nurses.

"Y*ou came really quickly",* a client said to a nurse after a fall incident. "*You cannot prevent a fall, but you can try to detect it as quickly as possible",* respondent 2 said.

The work efficiency increased because the optical A.I. sensors activated a night-time nurse only if an abnormal movement occurred in the client's room. In the same meeting, the cost-effectiveness of the sensors was discussed. If the optical A.I. sensors increased the work efficiency of night-time nurses, the experienced workload decreased. A decrease in the workload reduced the number of nurses required per night. However, the healthcare professionals in this meeting were careful in emphasising that the number of night-time nurses can be reduced. More pilot projects need to be done with the sensors over a longer period to conclude that work efficiency significantly increases with their use.

4.4 Adopter System

As the data suggests, the use of optical A.I. sensors resulted in more efficient work routines for night-time nurses, which means that the nurses had to change their work routines. However, night care was provided mostly alone. Therefore, as seen in the data, there needed to be a good backup in the form of a coordinating nurse when night care was provided alone.

The optical A.I. sensors did not take over the tasks of the nurses; they only decreased the number of tasks. The respondents indicated that the number of regular checks was decreased, as the nurses needed to check on a client only if the sensor sent an alarm. The work routine that needed to be changed was that nurses needed to carry out fewer regular checks. With the optical A.I. sensors, the nurses did not feel guilty if they did not see the clients for a few hours explained respondent 2. Respondent 7 indicated that nurses felt obligated to see clients by themselves. However, according to respondent 1, the nurses regularly checked on the clients for their own peace of mind. Respondent 7 experienced having more time for the clients during the night because of the sensors. If the night-time nurses provided fewer regular checks, they had more time for the clients who needed help, as showed by the data. Respondent 6 explained different types of disturbance during the night: restless clients and people who get sick or are going to the toilet. Respondent 4 listed additional types of disturbance: changing a stoma, clients who want to eat or drink, or clients who are afraid.

Working at night was a fairly solitary experience because night care was delivered by only one night-time nurse at a time. This solitary experience resulted in more absenteeism. Working alone reduced camaraderie. "E*mployees who are working on different residences and* *teams are having more absenteeism",* respondent 3 said. However, respondents 1, 2, and 3, independently of each other, did not notice more absenteeism when people worked at night. In addition, as a result of this solitary experience, discussing and sharing the workload became tougher. The night-time nurses needed to call the coordinating nurse to discuss or ask for help with care delivery, making delivering patient-centred care harder. Respondent 7 explained, "*Sometimes you want to give someone extra attention because they have certain concerns. Unfortunately, you often have to interrupt that conversation because you need to provide care in another room".* For these types of moments, an extra night-time nurse would be appreciated but not necessary because of the short period this extra nurse was needed. Another consequence of working alone at night was that nurses felt more responsible to go to their work. They knew how difficult it could be to cover the night shifts. For this reason, some nurses experienced having a higher threshold to call themselves in sick before a night shift. "*If there are two nurses, you have an extra backup when you are sick",* respondent 6 explained.

Data suggests that, nowadays, there are many tools to help nurses provide care alone, for example, ceiling elevators. These tools have made it possible for night-time nurses to take care of clients during the night alone. In a case of emergency, night-time nurses could always call a coordinating nurse from another location who would come as soon as possible. Therefore, it must be ensured that the night-time nurses can fall back on the coordinating nurse. As the data suggests, the coordinating nurses need to be located near the different locations of other nurses. "*If someone fell down, you still have to get them off the ground by yourself. It will take a while before the coordinating nurse is at your location"',* said respondent 6. For this reason, night-time nurses did not call the coordinating nurse often. "*I will do it myself",* explained respondent 7.

4.5 Organisation

As the data shows, night-time nurses needed to trust the optical A.I. sensors before the nurses were able to adopt new work routines. The sensors activated a nurse to check a room during the night only if the client performed an abnormal movement. Consequently, the night-time nurse did not have to check on the client for the rest of the night.

The optical A.I. sensors were implemented at one location. At this location, the night-time nurses were checking on clients with dementia at least two or three times a night, according to respondent 6. Respondent 2 indicated that nurses were aware that they woke up clients during their regular checks. However, they did not have a solution to tackle this problem. According to respondent 4, the sensors could not see the difference between a client who was awake and one who was asleep. According to the data, if the sensors were able to see the difference, it would improve the delivery of patient-centred care and the adaptation of the sensors by the nurses. The nurses explained that clients had delusions of fear at night. Respondent 10 explained that a night-time nurse could provide help in this situation by hearing the client's story. However, to deliver such patient-centred care, it was important to know which clients were awake.

As the data suggests, trusting and seeing the benefits of the sensors improved the adoption. Respondent 7 explained, *"At first, I did not trust it. Until recently, when I got a notification that someone had fallen".* The data shows that the night-time nurses must gain confidence in the optical A.I. sensors and see them in action before they can adjust their tasks. Respondents 2 and 3 indicated that time was needed to create this trust. According to the data, for most night-time nurses, it took a few nights for them to trust the system.

The nurses needed to experience the added value of the optical A.I. sensors before they could adopt new tasks. During several meetings, it became clear that the organisation took the process changes into account from the beginning. It was observed that the optical A.I. sensors activated the night-time nurses to perform a task when needed. As a result, it reduced the number of tasks because the night-time nurses did not need to observe by themselves which clients needed extra help. As seen in the data, night-time nurses could work more efficiently. The improved work efficiently could result in one less night-time nurse during the night.

4.6 Wider Context

Due to healthcare professionals working more efficient, the optical A.I. sensors are becoming more cost-effective. The cost-effectiveness increases the willingness to implement and spread the technology in a wider context. However, healthcare professionals had, especially at the beginning of the implementation of optical A.I. sensors, a "Big Brother" feeling.

Data shows that the sensors activated the night-time nurses to perform a task when a client needed it, reducing the number of tasks as a result. Thus, night-time nurses were able to work more efficiently, which resulted in a reduction in the number of night-time nurses required per night. However, the data also shows that this is an important consequence for the future. The population of elderly are growing. Especially in Zeeland, where the organisation provides long-term elderly care. During one of the meetings, the expectation was expressed that the shortage of employees will strongly increase in the region in the coming years. Respondent 2 emphasised that the fact that one night-time nurse would be sufficient to cover a night shift would be an advantage. Respondents 10 and 11, however, individually saw these process changes as a matter of costs. The feeling of healthcare professionals being replaced by technology was also expressed during a meeting before the optical A.I. sensors were implemented.

Respondent 1 said that the privacy of clients was violated by the sensors. However, respondent 1 continued that no images were stored and that the optical A.I. sensors captured only the contour. Furthermore, when a night-time nurse entered the room during the night, it was also an invasion of privacy, respondent 2 explained. Respondent 3 said that it was up to the client and their relatives to decide if the optical A.I. sensor was more invasive than the regular checks provided by the night-time nurses. So far, respondent 2 said, every client has permitted the use of optical A.I. sensors.

Some night-time nurses experienced feelings of extra control. Respondent 7 called the optical A.I. sensors a "Big Brother" tool. Respondent 5 paid extra attention to how she entered the room. Respondent 8 said, *"At the beginning, you feel a little bit watched".* The night-time nurses knew they would not be controlled by anyone. However, the data shows that there was some distrust in the beginning. According to respondent 8, nowadays, healthcare professionals do not even notice the optical A.I. sensors.

4.7 Embedding and Adaptation Over Time

The organisation wanted to spread the technology to more locations. However, during one of the meetings, it became clear that the potential pilot location was not willing to adopt its work routines to the optical A.I. sensors due to different aspects. The nurses appreciated the benefits of the sensors. However, the data shows that night-time nurses felt replaced by the technology, which also felt insulting. This feeling indicated the level of willingness of supporting new technologies. They were also defensive about the idea of working the night shifts alone. *"Because it wasn't highlighted on how nice the system works and we are going to see how care can become safer, but it was mainly emphasised on: We are going to investigate* *how you can work with fewer night care workers"*, respondent 2 explained. "*Then I would be helping to cut myself off",* respondent 10 said. Respondent 4 added that some nurses also said that they would look for another job if the sensors got implemented. One of the biggest objections to working alone was that night-time nurses could no longer ask a colleague for help. However, asking a colleague for help would still be ensured by the coordinating nurse at distance. Respondent 5 explained that the idea of the change from two to one night-time nurse could be threatening. This critical event was discussed during one of the meetings. The organisation had responded resiliently to this event and agreed that another location of the organisation would continue implementing the optical A.I. sensors. During one of the meetings, it was discussed that the introduction of the sensors should happen differently. It was decided that a project group would be set up with the night-time nurses from location three but also with a night-time nurse from the location where the optical A.I. sensors were implemented. This night-time nurse was seen as the ambassador by those present at the meeting. The "ambassador" nurse, from their own experience, could help the other night-time nurses with the implementation and adoption of the optical A.I. sensors. The study was too short to analyse the effects of this ambassador.

Chapter 5. Discussion and Conclusion

The study provides interesting insights into the use of optical A.I. sensors. The experiences of healthcare professionals emerged through the interviews. A better sleep quality, a higher safety level for clients, and more efficient healthcare professionals are all major benefits. However, this study also shows the conditions and the resistance to the consequences of implementing technology from healthcare professionals. In addition, the areas for improvement for optical A.I. sensors are highlighted to further improve them to be of a higher value to healthcare professionals.

First, a critical reflection on the findings is provided. Second, the contribution to the existing literature is explained. Third, the limitations of this study are taken into account. Fourth, recommendations for further research are provided. Fifth, practical recommendations for the organisation about the implementation of the optical A.I. sensors are listed, and, finally, an answer to the research question is provided in the conclusion.

5.1 Critical Reflection on Findings

The results of this study indicate that clients with dementia wake up easily when a night-time nurse checks on them. This finding is in line with the findings of the study of Webster et al. (2020) that clients with dementia experience more sleep disturbance. Reducing the number of regular checks increased the sleep duration of clients. Better sleep quality can decrease the symptoms of dementia (Arvantakis & Bennett, 2019). However, as the data shows, if a client with dementia woke up during the night, they did not have the awareness that they could call a night-time nurse when needed. The optical A.I. sensor took over the alarming process, which resulted in a direct alarm to the night-time nurse. Hall et al. (2019) stated that this direct alarm increased clients' safety.

What the optical A.I. sensors saw as a normal and an abnormal movement was customised per client. This was necessary because the risks of falling, for example, have different personal causes, as explained in different studies (Dhargave & Sendhilkumar, 2016; Kröplin et al., 2013). Because the optical A.I. sensors were customised and they reduced the number of regular checks if the night-time nurses adopted them, this study concludes that the self-control of clients increases. Clients got the opportunity to walk around in their own room, without being controlled of a night-time nurse who was checking the rooms. The regular checks of the night-time nurses violate the privacy of the clients. However, Hall et al. (2019) concluded the opposite, that not the nurses decreased the own control and privacy of clients, but the technology did. The so called “on” technology is measuring the motion of clients every moment.

Optical A.I. sensors can improve the work process of healthcare professionals (Van der Meulen, 2019), which is in line with the results of this study. The sensors did not take over the tasks of the night-time nurses. In contrast, it reduced the number of tasks because the night-time nurses were not obligated to manually check on every client every few hours. As a result, the nurses experienced having more time for clients who needed help during the night because of the sensors. The extra time improved the client–nurse relationship, which is in line with the study of Hall et al. (2019), which found that relevant and on-time care improves this relationship. However, Engström et al. (2009) concluded that the care delivery would be less patient-centred due to technology. Night-time nurses may get an extra workload and be afraid to lose control over the care they deliver. The results of this study show that healthcare professionals are afraid to lose their jobs due to the optical A.I. sensors. However, this result is in line with the studies of Meijnckens (2016) and Van Gorp and Mulder (2018), which also concluded that healthcare professionals experience anxiety to lose their jobs because of technology.

During the meetings, it became clear that training was not necessary to work with the optical A.I. sensors. This is a contradictory result compared to the study of Engström et al. (2009), which emphasised the importance of sufficient training. The results of this evaluation show that the experience with the sensors was more important than training for the nurses to adopt the technology. The NASSS framework partly addresses what adopters need to adopt new technology. The framework focusses on the necessary knowledge and experiences of the adopter system. However, this study shows that certain emotions are also involved in adopting technology. Practitioners explaining their experiences and feelings about the technology can speed up the implementation of technology.

If a technical error occurred, it was passed on to the developer of the optical A.I. sensors, which means that the night-time nurses did not need to have extensive knowledge about the technology. The most important aspect for the nurses to work with the optical A.I. sensors was that they must gain confidence in the sensors and see the sensors in action before they can adjust their tasks. However, Gaube et al. (2021) concluded that this balance between trust and non-trust is necessary for a positive implementation.

Greenhalgh et al. (2017) developed the NASSS framework, which was used in this study to evaluate the implementation of optical A.I. sensors in the long-term care setting. The NASSS framework contains seven interacting domains, which are all important for the adoption and spread-up of technology (James, Papoutsi, Wherton, Greenhalgh, & Shaw, 2021). Other frameworks and studies about the implementation of technology mostly focus on one of the seven subjects Greenhalgh et al. (2017) used in their framework (James et al., 2021). For example, the technology acceptance model focuses more on the adopters; the perceived usefulness and perceived ease of use determine the adaptation of the technology (Ibrahim et al., 2017). The NASSS framework can be used to include different viewpoints of the implementation, which highlights the complexity of implementing technology in the healthcare setting (James et al., 2021). However, there is limited data about several domains, especially the domains “wider context” and “embedding and adaptation over time”, which form the two outer layers of the framework.

In this study, it was not possible to go into each domain in depth. The domains “wider context” and “embedding and adaptation over time” require a broader research context. For example, a political decision-maker should be included to more thoroughly cover the wider context (Banck & Bernhardsson, 2020). In addition, this study was conducted at the beginning of the implementation of the optical A.I. sensors and included only a few locations. For this reason, not much can be said about the domain “embedding and adaptation over time” (Banck & Bernhardsson, 2020). Nevertheless, these are important domains for identifying implementation and adoption over a longer period and in a broader scope. In addition, more research on these two outer sheets is necessary to provide a clear viewpoint.

Dividing the results by the different domains of the NASSS framework proved to be difficult. During this study, it was found that several topics from different domains overlapped each other. The choice of where to place the adopted work routines proved to be a difficult one, for example. In this study, the choice was made to place the adopted work routines under the domain of the adopter system because the healthcare professionals had to make these adoptions individually.

5.2 Contribution to Existing Literature

This study contributes to the knowledge about the implementation and adoption of optical A.I. sensors in long-term elderly care. It provides insight into the experiences of healthcare professionals with the implementation and adoption of optical A.I. sensors, which few research studies have assessed so far.

The NASSS framework of Greenhalgh et al. (2017) was used to address the implementation and adoption of the optical A.I. sensors. However, having trust in the optical A.I. sensors appeared to be an important aspect in the adoption of new task routines by healthcare professionals. In the NASSS framework, the aspect of trust in the technology is lacking. This aspect of "trusting the technology" should be taken into account when a new technology needs to be implemented and adopted. Components of the technology acceptance model address the missing piece of trust in the NASSS framework. It addresses the user beliefs the technology improves performance (Opoku, 2020). Therefore, it was useful to add some parts of the technology acceptance model to cover the aspect of trust in the domain "adopter system" of the NASSS framework.

Secondly, the willingness to adopt is an important aspect. In the future, the staff shortage of healthcare professionals will probably further increase (Van der Meulen, 2019). The elderly population will increase, especially in Zeeland. In addition, the population of working people will decrease. There will be a gap between the amount of elderly and the working population, who need to take care of the elderly. Optical A.I. sensors can help to narrow this gap in night-time care. However, these shortages were not experienced by the interviewed healthcare professionals. If this shortage is experienced, the willingness to adopt technology will perhaps increase. In addition, the technology needs to have benefits for clients and should not take healthcare professionals extra time to learn; when this is the case, healthcare professionals are more willing to adapt their task routines. The healthcare professionals observed an increase in the clients' quality of sleep and safety level. These observations made the night-time nurses more willing to work with the optical A.I. sensors and to adapt their work routines. Healthcare professionals need to know *why*, not just *how,* they need to adapt their task routines, as the NASSS framework states. Taking the benefits for both clients and healthcare professionals into account in the NASSS framework is recommended, as it makes healthcare professionals more open to adapting their task routines.

The ability of optical A.I. sensors to distinguish clients who are asleep from those who are awake would stimulate the adopting process for healthcare professionals. Optical A.I. sensors cannot make this distinguishment at the moment. If the sensors do not improve, the implementation and adoption in the long-term care setting will be harder. Nevertheless, De Chazal, O'Hare, Fox, and Heneghan (2008) researched a biomotion sensor that can distinguish between sleep and wake patterns; 69% of the wake pattern was identified correctly, compared to 88% of the sleep pattern (De Chazal et al., 2008). Casaccia, Braccili, Scalise, and Revel (2019) concluded that sensors can better detect a person who is awake than distinguish between the different sleep phases, for example, the rapid eye movement (REM) sleeping phase or a deep sleeping phase. However, to improve the optical A.I. sensors, the sensors do not need to distinguish the different sleep phases; differentiating between being awake and being asleep would be sufficient. The latest paper of Heglum et al. (2021) investigated the potentials of a sensor that distinguishes sleeping and being awake. The sensor can detect body movements. Heglum et al. (2021) concluded that based on an algorithm, body movements can provide information about whether a client is asleep or awake (Heglum et al., 2021). The accuracy of the differences between patients who were asleep and those who were awake was 81%. However, the validity of the sensors of Heglum et al. (2021) needs to be investigated further.

The current uptake of technology in long-term elderly care is limited, notwithstanding its potential (Van Gorp & Mulder, 2018). The COVID-19 pandemic, which started in 2020, increased the use of technology in the healthcare setting. In the United States, for example, the COVID-19 pandemic resulted in the fast adoption of telehealth across the healthcare sector (Dewar, Lee, Suh, & Min, 2020; Madden et al., 2020). The study of Conroy, Krishnan, Mittelstaedt, and Patel (2020) showed the benefits of technology to decrease loneliness among the elderly population. Technology is beneficial to remain in contact, but it also offers different opportunities to deliver healthcare, for example, online therapy (Conroy et al., 2020). However, Conroy et al. (2020) concluded that the adopters need to be trained to work with the technology before it can be used beneficially.

5.3 Limitations

There were some limitations of this study. First, at the beginning of this study, a choice was made to include only the domains "condition", "the adopter system", and "technology". Later, it became clear that it would have been better to include all of the domains of the NASSS framework. However, respondents cited various aspects of other domains, for example, the efficiency improvements of their work routines, the importance of the coordinating nurse who is the backup for the night-time nurses, and the fact that, when the benefits for clients and healthcare professionals become visible, the optical A.I. sensors get more support from healthcare professionals. The various cited aspects made these topics relevant to discuss further. The topic list was based on the domains “condition”, “the adopter system”, and “technology”. However, it had overlap with the other domains of the NASSS framework. If this topic list contained more specific domains of the NASSS framework, other relevant topics might have emerged, which are lacking in this study now.

Second, the study was conducted over a short period. The data was collected in only two months. This short period also made it harder to gather relevant respondents and conduct several interviews. As a consequence, the number of respondents was low. Only two locations of SVRZ were targeted as the research population for this study. Including other long-term elderly care organisations that have optical A.I. sensors could improve the generalisability. Nevertheless, eleven interviews with healthcare professionals of different disciplines were conducted at the end of this study. In addition, a case study that included one organisation was conducted. All respondents were healthcare professionals, which reduced the number of perspectives. Clients or informal caregivers might provide different information about their experiences with the optical A.I. sensors. However, clients and their informal caregivers did not have to adopt certain tasks because of the optical A.I. sensors. Therefore, interviewing only healthcare professionals was the right choice for this study.

Getting in touch with the night-time nurses of the location where the pilot was cancelled was difficult. Multiple emails were sent, and several contact details were collected; however, only one night-time nurse was open for an interview. After contacting the team leader, another nurse agreed to do an interview. However, this nurse worked night shifts occasionally. This limitation had no far-reaching consequences for the value of this study. This study focuses on the experiences of healthcare professionals with the implementation and adoption of optical A.I. sensors. Respondents had different backgrounds and perspectives, which allowed valid conclusions to be drawn.

In the end, the limitations do not affect the validity and reliability. Due to the triangulation of literature and interviews with a topic list, validity is ensured. This research took place during the COVID-19 pandemic. This could have influenced the perspectives of healthcare professionals, for example, on the experienced workload. However, the methods were described clearly, ensuring the reliability of this research.

5.4 Recommendations for Further Research

Further research on the optical A.I. sensors is important to improve the implementation and adoption in more long-term elderly care settings. Future research should focus on how the sensor can distinguish a client who is asleep from one who is awake. If optical A.I. sensors can learn this difference, they will perhaps be adopted faster by healthcare professionals; in addition, optical A.I. sensors will result in even more efficient working of healthcare professionals. Furthermore, healthcare professionals will feel less guilty to see a client less often. If the client is awake, the nurse gets activated by the optical A.I. sensors to check on the client. However, it is important to question if clients are allowed to be lying awake undisturbed. It should also be considered whether a nurse should go directly to a client when the client is awake at night. Clients must retain self-control.

After the results of this study, it is necessary to take a closer look at the role of the wider healthcare system in the current uptake of technology in healthcare. In addition, the adaptation and embedding over time should be investigated further. Informing healthcare professionals clearly about the A.I. system, conducting a business case, and gaining the trust of healthcare professionals are necessary steps in the implementation process. However, little is known about the role of the wider context and the embedding and adaptation over time. The NASSS framework of Greenhalgh et al. (2017) can be used as well. Being aware of the different disciplines in the implementation and adoption of healthcare technology is necessary to improve the current uptake of technology.

5.5 Practical Recommendations

In this section, different practical recommendations are made to improve the implementation and adoption of optical A.I. sensors in long-term care. First, clear communication is necessary to improve the implementation and adoption. Explaining the technology of optical A.I. sensors can be difficult. However, the goal of the optical A.I. sensors should be clear for every healthcare professional. Healthcare professionals should know what knowledge the technology adds and the type of additional knowledge healthcare professionals should have. Facilitating communication face-to-face can be beneficial. Consequently, the trust of healthcare professionals in the implementation of optical A.I. sensors will increase.

The second recommendation is about the benefits of the optical A.I. sensors. Healthcare professionals have indicated that they first need to experience the optical A.I. sensors before they can trust the system. This study recommends that healthcare professionals should be allowed to work with the optical A.I. sensors at a long-term care location. In this way, healthcare professionals can experience the optical A.I. sensors and the adopted work routines before they start working with the sensors at their work location. As a result, they will be more enthusiastic about the sensors because they will have experienced the way the sensors work in advance. Improvements in efficacy, safety, and desirability will be experienced by the healthcare professionals beforehand. As a result, healthcare professionals will have more trust in the technology. This trust is important for healthcare professionals to change their roles, practices, and identities earlier in the implementation.

The final recommendation for long-term care is that organisations should focus on locations with more than two night-time nurses per night. The optical A.I. sensors increase the work efficiency, and, with it, the workload decreases at the residences of dementing clients. The improved work processes can, as a consequence, require night-time nurses to adapt their tasks and work with one less night-time nurse. However, healthcare professionals explained that a reduction from two to one night-time nurse can be frightening. If the optical A.I. sensors are placed at a location with more night-time nurses (e.g., four), the reduction of one night-time nurse can be experienced as less frightening. In the end, there would still be two colleagues available to ask for help or advice, and the cost-effectiveness would be maintained. However, if this is not possible, it is necessary to have a coordinating nurse as a backup. This coordinating nurse must be present within a short driving distance to ensure a good backup. In addition, the organisation should be aware of the capacity to innovate and the involved work, which is needed for implementing technology. It should also be aware of the financial and regulatory requirements implementing a new technology involves.

5.6 Conclusion

The research question of this study was, *“What are the experiences of healthcare professionals with the implementation of optical A.I. sensor technology for night-time care delivery in a long-term care setting?”*

Because of optical A.I. sensors, clients slept better and were more at ease at night. The sensors increased the safety of clients because nurses were activated when a client performed an abnormal movement. In addition, the nurses could work more efficiently because of the optical A.I. sensors. They checked on clients less often during the night, which resulted in decreased work pressure, more time for a casual chat with a client who was awake. Moreover, nurses felt less guilty about not seeing a client for a few hours during the night. In addition, the sensors were customised for every client, which further increased patient-centred care delivery. When the sensors were installed, the nurses received a short demonstration. However, the sensors were not difficult to understand. Nevertheless, nurses should get the opportunity to develop trust in the technology before they can adjust their tasks. To gain more trust from the night-time nurses, the optical A.I. sensors should be improved, which will result in even more efficient work. It would add value for the nurses if the sensors could distinguish clients who were sleeping from those who were awake. If the nurses could get an alarm if someone was awake, they could go for a check and chat. Healthcare professionals think that the optical A.I. sensors will enhance patient-centred care delivery. A critical consideration here is whether clients do not have the right to lie awake at night undisturbed.

However, clear communication about the technology and its implementation is necessary for healthcare professionals to gain trust. Healthcare professionals were afraid to lose their jobs because of the optical A.I. sensors. During the introduction to the optical A.I. sensors, healthcare professionals experienced a lot of emphasis being put on improved work processes, which was interpreted by them as too much focus on costs. The emphasize on increased work efficiency resulted in a great deal of resistance from healthcare professionals. They had the feeling that technology would take over their jobs and that they would be helping it do so.

Overall, the experience that healthcare professionals have with the optical A.I. sensors was positive. However, introducing and implementing optical A.I. sensors remains difficult. The NASSS framework can help an organisation to obtain an overview of all the different domains and viewpoints, which will contribute to the communication with healthcare professionals. In addition, it might be helpful to add a healthcare professional who has worked with optical A.I. sensors to the group from the location where the sensors are going to be implemented. This healthcare professional can share their own experience, which will develop trust in the optical A.I. sensors among other healthcare professionals and also help with the adoption and implementation of the optical A.I. sensors.

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Annex I Topic List

Introduction

- Introduce.
- Privacy (informed consent).
- Explain aim and content of the research.

Condition

- Extra risks for falling during the night (Vandenberg et al., 2017)
- Sleep pattern (Irwin & Vitiello, 2019)
- Daily activities (Irwin & Vitiello, 2019)
- Privacy versus extra risk (Greenhalgh et al., 2017)

Technology

- Information on how they work (Greenhalgh et al., 2017)
- Use of the optical sensors (Greenhalgh et al., 2017)
- Safety (Greenhalgh et al., 2017)
- Versus infrared motion sensors (Greenhalgh et al., 2017)

Value proposition

Adopter system

- Night occupancy-> shortage of nurses (Van der Meulen, 2019)
- Nurses working extra nights (Greenhalgh et al., 2017)
- Processes (Greenhalgh et al., 2017)
- Workload (Greenhalgh et al., 2017; Van der Meulen, 2019)
- Negative effects of working night shifts (illnesses) (Van der Meulen, 2019)
- Consequences of optical sensors for the care (Greenhalgh et al., 2017)
- Consequences of optical sensors for the clients (Greenhalgh et al., 2017)

Organisation

Wider context

Embedding and adaptation over time

In summary

- Want to work with optical sensors
- Future perspective on optical sensors (A.I.)

Conclusion

- Important subjects
- Thank

Annex II NASSS Framework

Domain/ question	Simple	Complicated	Complex
Domain 1: the condition or illness			
1A. What is the nature of the condition or illness?	Well-characterised, well-understood, predictable	Not fully characterised, understood, or predictable	Poorly characterised, poorly understood, unpredictable or high-risk
1B. What are the relevant sociocultural factors and comorbidities?	Unlikely to affect care significantly	Must be factored into care plan and service model	Pose significant challenges to care planning and service provision
Domain 2: The technology			
2A. What are the key features of the technology?	Off-the-shelf or already installed, freestanding, dependable	Not yet developed or fully interoperable; not 100% dependable	Requires close embedding in complex technical systems; significant dependability issues
2B. What kind or knowledge does the technology bring into play?	Directly and transparently measures (changes in) the condition	Partially and indirectly measures (changes in) the condition	Link between data generated and (changes in) the condition is currently unpredictable or contested
2C. What knowledge and/or support is required to use the technology?	Non or a simple set of instructions	Detailed instructions and training needed, perhaps with ongoing helpdesk support	Effective use of technology requires advanced training and/or support to adjust to new identity or organisational role
2D. What is the technology supply model?	Generic, 'plug and play', or COTS solutions requiring minimal customisation; easy	COTS solutions requiring significant customisation or bespoke solutions; substitution difficult if supplier withdraws	Solutions requiring significant organisational reconfiguration or medium- to large scale-bespoke

	substitutable if supplier withdraws		solutions; highly vulnerable to supplier withdrawal
Domain 3: The value proposition			
3A: What is the developer's business case for the technology (supply-side value)?	Clear business case with strong chance of return on investment	Business case underdeveloped; potential risk to investors	Business case implausible; significant risk to investors
3B: What is its desirability, efficacy, safety, and cost effectiveness (demand-side value)?	Technology is desirable for patients, effective, safe, and cost effective	Technology's desirability, efficacy, safety, or cost effectiveness is unknown or contested	Significant possibility that technology is undesirable, unsafe, ineffective, or unaffordable
Domain 4: The adopter system			
4A. What changes in staff roles, practices, and identities are implied?	None	Existing staff must learn new skills and/or new staff be appointed	Threat to professional identify, values, or scope of practice; risk of job loss
4B. What is expected of the patient (and/or immediate caregivers)-and is this achievable by, and acceptable to, them?	Nothing	Routing tasks, e.g. log on, enter data, converse	Complex tasks, e.g. initiate changes in therapy, make judgements, organise
4C. What is assumed about the extended network of lay caregivers?	None	Assumes a caregiver will be available when needed	Assumes a network of caregivers with ability to coordinate their input
Domain 5: The organisation			
5A. What is the organisation's capacity to innovate?	Well-led organisation with slack resources and good managerial	Limited slack resources; suboptimal leadership and	Severe resource pressures (e.g., frozen posts); weak leadership and

	relations; risk taking encouraged	managerial relations; risk taking not encouraged	managerial relations; risk taking may be punished
5B. How ready is the organisation for this technology-supported change?	High tension for change, good innovation-system fit, widespread support	Little tension for change; moderate innovation-system fit; some powerful opponents	No tension for change; poor innovation-system fit; many opponents, some with wrecking power
5C. How easy will the adoption and funding decision be?	Single organisations with sufficient resources; anticipated cost savings; no new infrastructure or recurrent costs required	Multiple organisations with partnership relationship; cost-benefit balance favourable or neutral; new infrastructure (e.g., staff roles, training, kit) can mostly be found from repurposing	Multiple organisations with no formal links and/or conflicting agendas; funding depends on cost savings across system; costs and benefits unclear; new infrastructure conflicts with existing; significant budget implications
5D. What changes will be needed in team interactions and routines?	No new team routines or care pathways needed	New team routines or care pathways that align readily with established ones	New team routines or care pathways that conflict with established ones.
5E. What work is involved in implementation and who will do it?	Established shared vision; few simple tasks, uncontested and easily monitored	Some work needed to build shared vision, engage staff, enact new practices, and monitor impact	Significant work needed to build shared vision, engage staff, enact new practices, and monitor impact
Domain 6: The wider context			
6A. What is the political, economic, regulatory, professional (e.g., medicolegal), and	Financial and regulatory requirements already in place nationally; professional bodies	Financial and regulatory requirements being negotiated nationally; professional and lay	Financial and regulatory requirements raise tricky legal or other challenges; professional bodies

sociocultural context for program rollout?	and civil society supportive	stakeholders not yet committed	and lay stakeholders unsupportive or opposed
Domain 7: Embedding and adaptation over time			
7A. How much scope is there for adapting and coevolving the technology and the service over time?	Strong scope for adapting and embedding the technology as local need or context changes	Potential for adapting and coevolving the technology and service is limited or uncertain	Significant barriers to further adaptation and/or coevolution of the technology or service
7B. How resilient is the organisation to handling critical events and adapting to unforeseen eventualities?	Sense making, collective reflection, and adaptive action are ongoing and encouraged	Sense making, collective reflection and adaptive action are difficult and views as low priority	Sense making, collective reflection, and adaptive action are discouraged in a rigid, inflexible implementation model

Table 1 NASSS framework elaborated (Greenhalgh, et al., 2017)