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How to Interact with Augmented Reality Head Mounted Devices in Care Work? A Study Comparing Handheld Touch (Hands-on) and Gesture (Hands-free) Interaction

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How to Interact with AR Head Mounted Devices in Care Work? A Study Comparing Handheld Touch (Hands-on) and Gesture (Hands-free) Interaction

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Abstract:

In this paper, we investigate augmented reality (AR) to support caregivers. We implemented a system called Care Lenses that supported various care tasks on AR head-mounted devices. For its application, one question concerned how caregivers could interact with the system while providing care (i.e., while using one or both hands for care tasks). Therefore, we compared two mechanisms to interact with the Care Lenses (handheld touch similar to touchpads and touchscreens and head gestures). We found that head gestures were difficult to apply in practice, but except for that the head gesture support was as usable and useful as handheld touch interaction, although the study participants were much more familiar with the handheld touch control. We conclude that head gestures can be a good means to enable AR support in care, and we provide design considerations to make them more applicable in practice.

Keywords: Care, Augmented Reality, Head Mounted Devices, Head Gestures.

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1 Introduction: AR in (Home) Care

Many societies today feature an aging population. As a result, the number of people that require care continues to grow (Schorch, Wan, Randall, & Wulf, 2016). However, despite their importance, care workers remain in short supply (Bratteteig & Wagner, 2013). As a result, they need to provide care in less and less time. Accordingly, researchers have widely discussed using IT in care to disburden and support care workers (see, e.g., Ackerman, Goggins, Herrmann, Prilla, & Stary, 2018b).

In many cases, professional caregivers do not exclusively provide care. Instead, *caring* often means that relatives and professional caregivers *share* the work between them. Factors such as the shortage in caregivers due to demographic changes (especially in many Western European and Asian societies), the economic pressures that many relatives of patients that need care face, emotional bonds, and the perception of responsibility to care for a beloved relative create situations in which both professional and nonprofessionals care for patients. In many cases, patients' relatives such as spouses, children, parents, and others become informal caregivers and conduct basic care tasks such as washing, dressing, and, after receiving education to do so, even more advanced care tasks (González-Fraile et al., 2015; Güldenpfennig, Nunes, & Fitzpatrick, 2015; Schorch et al., 2016; Wüller, Behrens, Garthaus, Marquard, & Remmers, 2019; Zarit, Pearlin, & Schaie, 2019). Informal caregivers need guidance and safety to ensure they provide good care. Further, in situations where professional and informal caregivers provide care, they need to share the work and the information needed for it (Amsha & Lewkowicz, 2015).

The challenges we mention above also put care organizations under pressure since they can find it more and more difficult to provide high-quality care to all patients. Therefore, it is widely acknowledged that future (and current) care needs to rely on different (business) models. Such models include professional and informal caregivers who closely cooperate with each other. Moreover, technology will have to take a larger role in care, and it will change the way caregivers conduct care (Bossen, 2018). For example, the literature has discussed technology to help individuals care for themselves (Ackerman, Büyüktür, Hung, Meade, & Newman, 2018a), technology that enables care networks (Bratteteig & Wagner, 2013), virtual reality (VR) and augmented reality (Mather et al., 2017; Wüller et al., 2019), and human-robot teams in care (Lee et al., 2018; Poulsen & Burmeister, 2019). Thus, future care and its (business) models will depend on a care organization's ability to integrate technology into its processes to maintain a high-quality care (Ackerman et al., 2018b).

In this paper, we describe a system called Care Lenses that supports informal and professional caregivers by using augmented reality. This work forms part of a larger research project that investigates the feasibility and potential benefits of using augmented reality support for care. We developed Care Lenses, a head mounted device (HMD) to support care workers via AR, to ease care work and enhance care quality. The project builds on an ethnographic study of care practices from which we identified support fields and matched them with the specific AR affordances (specifically HMDs), which resulted in a set of features. Together with caregivers, we built working prototypes of these features and studied them in practice. We conducted the project to contribute to overcoming current challenges in care by providing support to caregivers in order to help transform care to future models as we discuss above and maintain high-quality care.

In many care situations, caregivers need one or both hands to interact with a patient or use assistive equipment. Therefore, we developed a mechanism that allows caregivers to control Care Lenses with head movements ("head gestures"); that is, without the need to use their hands for gestures or controls. In this paper, we report on a study in which we compared this mechanism with a built-in touch-based HMD.

With this paper, we contribute to the literature by presenting and evaluating the head gesture interaction mechanism for HMDs in care practice. This novel concept makes HMDs applicable in healthcare when caregivers need both hands for treatment, and our work shows that it works well in practice. In addition, we introduce Care Lenses and show the potential benefit of the concept for providing care. To the best of our knowledge, the Care Lenses system represents a unique concept that applies HMDs in healthcare as it supports various care tasks in practical care. However, note that, although we conducted the study we present here with professional caregivers, informal caregivers can also use Care Lenses to provide care, which we discuss in later sections.

2 Related Work

2.1 Augmented Reality to Support Work

Azuma (1997) has stated that augmented reality (AR) superimposes virtual objects on or composites them with the real world, and, thus, that “AR supplements reality, rather than completely replacing it” (p. 356). By using AR devices, users enter what Milgram and Kishino (1994) call “mixed reality” (MR), which merges digital and real worlds. Researchers have found AR useful for supporting work in various domains and for various purposes, including remote (expert) support (Fakourfar, Ta, Tang, Bateman, & Tang, 2016; Johnson, Gibson, & Mutlu, 2015), guidance (Büttner et al., 2017), remote cooperation (Datcu, Lukosch, & Lukosch, 2016) and (remote) instruction or learning (Garrett, Jackson, & Wilson, 2015; Preuveneers, 2015). In most such examples, the authors have noted that AR enables users to interact with digital information and objects that support work tasks while looking at the work scenery. AR can show information for tasks or annotations attached to items (Fakourfar et al., 2016) and hints from a remote expert (Datcu et al., 2016). Therefore, with AR, IT support becomes an integral part of the work task.

One can implement AR in different types of devices such as mobile phones, tablets, or HMDs (often called “glasses” or “lenses”). While users commonly use handhelds and, therefore, offer better possibilities to access and use augmented reality, users need to use at least one hand (if not both hands) to hold and operate them. As such, one cannot easily use AR in some work areas, especially when a task needs both hands (Johnson et al., 2015). However, it remains unclear how one can best interact with HMDs to tap from the potential of hands-free mixed reality. Features offered for this interaction often depend on the hardware available (cf. Schmalstieg & Hollerer, 2016). Common means of interaction that current HMDs provide include swiping the HMD’s frame (e.g., Vuzix glasses), voice control, gestures, and gaze (e.g., Microsoft HoloLens, Google Glass), or additional handheld devices such as touchpads or clickers (e.g., Epson Moverio glasses and Microsoft HoloLens). Except for voice interaction, all these mechanisms require the user to use at least one hand actively interact with the device. Recently, some third parties have developed and used solutions for using eye-tracking in AR to interact with HMDs (e.g., Ku, Wu, & Chen, 2017; Kytö, Ens, Piomsomboon, Lee, & Billingham, 2018), but no off-the-shelf solution for this modality exists except for single-gesture solutions such as eye blinks on the Google Glass.

2.2 Head Gestures for Augmented Reality

A promising way to provide hands-free interaction involves using head movements as gestures to control AR and VR HMDs. By using HMDs’ built-in sensors such as accelerometers and gyroscopes, they can interpret and use distinct head movements as input commands. Researchers have investigated head movements as a mechanism to help people with disabilities control assistive technology (Jia, Hu, Lu, & Yuan, 2007; Rudigkeit, Gebhard, & Gräser, 2014). Further, research has looked at head movements as an easy-to-use and precise way to point to objects in mixed reality (Kytö et al., 2018), to authenticate oneself on HMDs (Yi, Qin, Novak, Yin, & Li, 2016), to track moving objects (Esteves et al., 2017), to mirror and explicate emotions (Terven, Raducanu, Meza-de-Luna, & Salas, 2016), and to interact with AR HMDs (Starner, 2013; Yi et al., 2016).

Researchers have investigated various specific gestures for interacting with virtual and augmented reality devices, such as nodding and shaking the head, turning the head to the side, looking up and down (and holding the head for a while after moving), tilting the head to the side, and leaning forward or backward (including the upper part of the body) (Ruban & Wood, 2016; Sharma, Ahmetovic, Jeni, & Kitani, 2018; Terven et al., 2016; Yi et al., 2016). To detect head gestures, HMDs can use either motion sensors such as accelerometers and gyroscopes (Starner, 2013) or video analysis (e.g., Sharma et al., 2018). Research has shown motion sensors to provide a low-cost but feasible method to detect and discriminate gestures (Yi et al., 2016). Head gestures have many advantages. For instance, many potential users know about them and, thus, can easily learn them. Further, people use them in everyday communication to convey meaning and, thus, can use them intuitively (Sharma et al., 2018; Yi et al., 2016). In addition, people can use head gestures easily and with good precision (Plaumann et al., 2015), and they provide a subtle means to interact with a system (rather than, e.g., voice control). Most importantly, head gestures allow one to interact with AR without using their hands at all.

2.3 AR Support for Care

AR continues to become more and more interesting for research and for developing support for healthcare work mainly due to, in Siebert et al.'s (2017) words, its potential to “free users’ hands and allow them to ‘see the scene through the screen’” (see also Kobayashi, Zhang, Collins, Karim, & Merck, 2018). This quote points to AR HMDs’ two main benefits in care. First, they provide information during the care process; thus, the user does not need to look up information in the documentation and, thus, interrupt the care process. Second, they allow caregivers to use their hands to provide care (see also Wüller et al., 2019).

Most head-mounted AR (and VR) applications in care contexts deal with education (e.g., Azimi et al., 2018; Garrett et al., 2015; Kobayashi et al., 2018). Zhu, Hadadgar, Masiello, and Zary (2014) overview how AR and VR can support healthcare education, and Kobayashi et al. (2018) show that the areas of AR training have grown. For using AR in medical training, Azimi et al. (2018) showed how AR-based training enabled medical professionals to increase their “time-on-task” and their confidence in what they did. AR can also provide remote (expert) guidance in care. Besides others, Mather et al. (2017) showed how their Helping Hands system supports caregivers in practice.

However, little work has examined how AR can support care tasks. Among the applications that AR support care directly, the SnapCat system that Aldaz et al. (2015) presented used Google Glass devices to take pictures of patients’ wounds to help document wound management in care. They argued that, without their system, visually documenting wounds needs at least two people to position the patient to make the wound visible, hold a ruler to document the size of the wound, and take a picture. They found that nurses preferred their system over traditional means to manage wounds, which they attributed mainly to hands-free documentation. Siebert et al. (2017) found that physicians who used HMDs to guide defibrillation and other tasks in resuscitation simulations performed as quickly as colleagues who used normal support but adhered much better to standard procedures and made fewer errors.

2.4 Open Issues and Research Question

The literature we discuss above shows the potential of AR HMDs in care and the need for this support. However, few studies have examined this support, and they have focused only on specific features as we show above. In addition, from these studies, we know little about how caregivers should work with AR support while physically (with their hands, moving the body) interacting with patients. Therefore, questions remain such as how to provide caregivers with interactive support while providing care and how they can interact with HMDs while providing care to patients.

We conducted our study to answer these questions. In particular, we directed our attention to the following research question (RQ):

RQ: How can head gestures help caregivers use AR HMD to provide care?

To answer this question, we compared head gestures to the well-known interaction with the touch pad attached to the Epson glasses. In Section 3, we describe our study’s methodology.

3 The Care Lenses

3.1 The Concept of Care Lenses

The Care Lenses support care processes and enhance care quality. We used AR to overcome the obstacle that caregivers cannot use mobile devices or other material while they provide care as they need their hands to provide care and to maintain hygiene. The support that the Care Lenses provide builds on field work and co-design with caregivers. During the field work, different researchers conducted an ethnographic study with 10 patients whom we observed over several days as they received care. In addition, we conducted 24 interviews with caregivers, care managers, and patients’ relatives. The insights few gained from these interviews informed how we designed the Care Lenses. First, we found that care workers’ practices differ individually and from one organization or department to the other. We also found that care needs to follow guidelines to guarantee care quality and patients’ wellbeing. In pain management, for example, caregivers ask patients to estimate their pain level, and caregivers need to make sure the patient is conscious enough to provide this estimation. Therefore, one cannot provide support for care tasks in a strict step-by-step way: it needs to allow caregivers to navigate flexibly through steps of their tasks while adhering to guidelines. Second, we saw that care is personal and needs physical interaction with patients. These tasks need one

or both the caregiver's hands to provide care, position the patient, or use auxiliaries needed for the specific care task (see also Aldaz et al., 2015). This factor served as a crucial constraint for the Care Lenses since they needed to provide support needs *while* the caregiver provided care (i.e., as the caregiver uses both hands). As an alternative, another caregiver could provide the support (from expertise or by reading from guidelines), but, given the shortage of personnel in care, caregivers rarely have access to such helpers. Thus, we derived a large set of support options that the Care Lenses could provide, such as care workflows (e.g., pain and wound management), documentation, assistive equipment ordering, and many others.



Figure 1. The Epson Moverio BT-300 HMD used for the Care Lenses and the Handheld Touch Controller (R)

We implemented the Care Lenses prototypes on an Epson Moverio BT-300 device (see Figure 1). We chose this device for multiple reasons. First, we wanted to use a binocular HMD as monocular HMDs may lead to additional cognitive and physical demands (e.g., Matthies, Haescher, Alm, & Urban, 2015). Second, many advanced HMDs such as the Microsoft HoloLens or the Meta 2 glasses are large and look like helmets rather than supportive glasses. Caregivers said that such devices might interfere with their personal relations with their often vulnerable patients. Third, the Epson glasses use a handheld touch device attached to the glasses. Since users know about touch devices from their laptops and mobile phones, we expected the device to provide less of a burden in our initial design cycles compared to devices that would work with other AR controls. In focus groups, however, we also found the latter problematic in cases in which caregivers needed both hands for care, which triggered the work we describe here.

The Care Lenses work in three phases: initiation, support provision, and documentation. The user initiates the lenses either by selecting a support feature from a menu or by context recognition. For the latter, the Care Lenses recognize markers placed in the patient room or objects such as assistive equipment. From this, they deduct usage contexts. For example, if they recognize a pain scale, the lenses offer support for pain management or ordering pain scales (see Figure 2 below). To provide support, the Care Lenses provide information for a task, step-by-step instructions for care tasks, or access to organizational features. The caregiver can access and control this support during care. The Care Lenses can also document certain tasks that it recognizes and help caregivers enter values into the care documentation (e.g., pain levels of patients, see below).

Note that we designed Care Lenses for occasional, task-driven use rather than constant, longer-term use (such as through a caregiver's entire shift). We focused on designing them to relieve caregivers from burdens rather than adding to work load by constantly providing them with information. In practice, we would expect caregivers to put on the Care Lenses for a certain task and take them off after conducting and documenting the task. This way, caregivers would not wear the Care Lenses for a long time, and many colleagues could share one device.

3.2 Sample Workflow Used in the Study: Pain Management

We chose a moderately complex workflow as we did not want to create a burden by providing caregivers with new technology *and* a workflow with high complexity. In addition, informal caregivers also likely had some training in. We found pain management an important and error-prone task in practice.

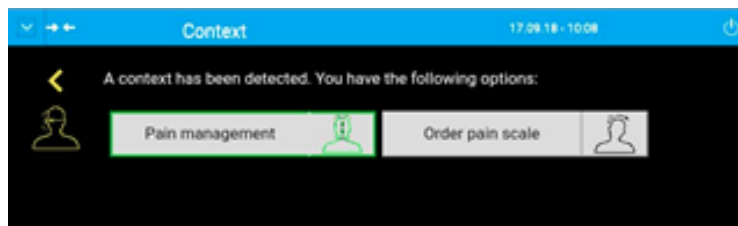


Figure 2. Starting the Workflow by Switching to the Right Button and Selecting it¹

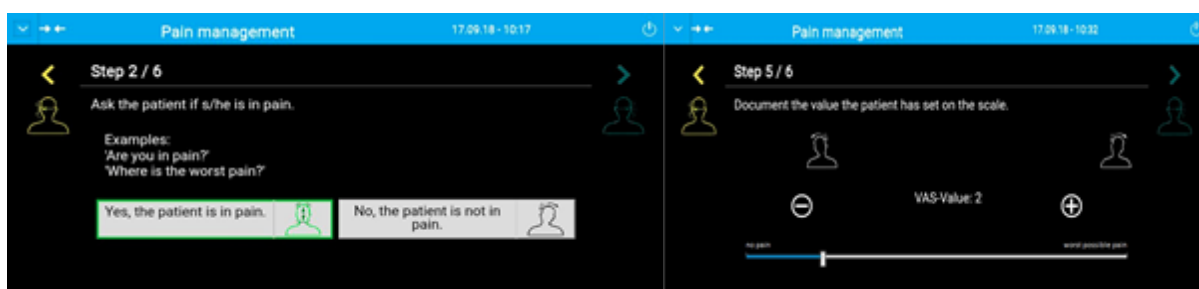


Figure 3. Guidance for Questions to Use in Pain Management (Caregivers Can Approve or Cancel the Workflow) (L); Entering the Pain Level by Tilting the Head (Icons Right/Left) (R)

The pain management workflow includes seven steps (see Table 1). It starts as Figure 2 shows with the pain-management context that the Care Lenses recognizes via, for example, detecting a pain scale. It then guides the caregiver through a process of asking patients whether they feel in pain to having them assess their pain level (Figure 3 left) and documenting this level (Figure 3 right).

Table 1. Steps of the Workflow

Step	Description
Start	Starting the workflow (button pre-selected)
1	Approving that the patient can act for herself
2	Suggestion of questions for approaching patients
3	Handing out the pain scale
4	Receiving the pain scale
5/5_2*	Entering the pain level selected by the patient
6/End	Results of the pain management process

* Includes the tilt gesture that Table 2 shows.

As Figure 3 shows, pre-selected buttons allow caregivers to approve the steps and to proceed. After assessing patients' pain level, caregivers enter it into the Care Lenses by tilting their head left or right to set the respective value (Figure 3 right). To make the interaction more demanding and to simulate a mistake that happens in practice, we included a loop into this workflow. After entering the value for the pain that the patient selected into the dialogue at step five and reaching step six, the patient told the caregiver he wanted to make a correction to the pain level. After that correction, the caregiver had to go back to step five (called step 5_2 in Table 1), change the value and go to step six again ("end" in Table 1).

¹ The black background of the screenshot is transparent when used on the Care Lenses.

3.3 Two Interaction Concepts to support Care Work with the Care Lenses

Our first interaction mechanism used the handheld touch device that comes with the Epson Moverio device. People's familiarity with this interaction type provides a good baseline to test other mechanisms with the Care Lenses. Despite this advantage, we assumed that the handheld would likely create problems in practice in which both caregivers need both hands for care tasks.

Recognizing the support needs and constraints in care, we wanted to provide a real hands-free interaction mechanism that allowed caregivers to use their hands permanently for care tasks. We considered various modalities to provide such interaction, such as eye tracking, head gestures, and voice control. Among these modalities, we discarded eye tracking because, when we conducted the study, only initial third party (add-on) devices to control AR HMDs and little research insights on them existed. We then decided for head gestures (and, thus, against voice control) in order not to disturb the relationship between the caregiver and the (often vulnerable) patient by having the caregiver speak commands into the HMD, which caregivers also mentioned as a concern in initial workshops. In contrast to voice commands, we considered gestures to not disturb patients as much. In addition, we wanted to avoid caregivers from accidentally activating commands when communicating with patients (cf. Yi et al., 2016). Note that we made this decision for our study in particular; we did not assess how well these mechanisms apply to care in general.

The Care Lenses detected gestures via inertial sensors (accelerometer and gyroscope) (for a similar approach, see Yi et al., 2016). In particular, these sensors detected the movement direction and speed along the coordinate axes using the corresponding rotation rates. To avoid the system from falsely detecting gestures when users simply moved their head, we used pre-set thresholds for head rotation and directions changes to detect gestures. We set these thresholds after a pre-test in which users tried different movement speeds to find the most appealing configuration as in Yi et al. (2016). For example, we recognized nodding by detecting quick up and down movements of the head with at least two direction changes.


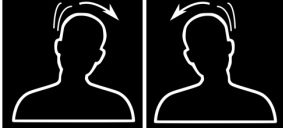


Further, we needed to ensure the HMDs we used recognized the gestures, and we wanted them to be as unobtrusive and natural (as they would be used in front of patients) and as intuitive as possible to lower the burden of using them (for these requirements, see Aldaz et al., 2015; Terven et al., 2016; Yi et al., 2016). We took gesture candidates from related work that considered recognizing, discriminating, and using such gestures.

From the workflow support that we decided on for the Care Lenses, we derived commands that head gestures would cover, such as starting a workflow and continuing to the next step (approving), going back and forth between steps, switching between buttons (for choices), setting values and cancelling a workflow. As the two most natural, distinct, and easy to detect (Ruban & Wood, 2016) head gestures, we selected nodding and shaking the head, which people intuitively associate with approval and disapproval or cancelling (Yi et al., 2016). We kept this association by using nodding for selecting and pushing buttons (e.g., acknowledging a step as in Figure 3) and head shaking for cancelling actions and returning to the home screen (see also Morency, Sidner, Lee, & Darrell, 2007). For the remaining features such as going forward and backward between the steps in the workflows (which the arrows in Figure 3 depict) and selecting buttons or setting values (switching buttons in Figure 2, setting values in Figure 3), we selected turning to the side and tilting (see Section 2.2) because they matched best to going back and forth in a workflow (turning the head; see also Jia et al. (2007)) and switching values (tilting the head; see also Crossan, McGill, Brewster, & Murray-Smith, 2009). We noted that tilting and turning the head takes more time than nodding and shaking the head. We then adapted the temporal scale and thresholds for detection (Sharma et al., 2018).

We pre-tested the resulting gesture set (see Table 2) and found that participants could execute and distinguish between the gestures well-test. From conducting the pre-test, we also eliminated other gestures: for scrolling pages or moving up and down, we initially used head-up and head-down movements. However, in the pre-tests, users had a hard time to differentiate these movements from nodding, so we dismissed this gesture (see Sharma et al., 2018, for a similar observation). Instead, we avoided vertical menu structures.

We implemented gestures such that the Care Lenses would recognize them on the spot; that is, with little to no response time. As Figure 2 and Figure 3 shows, we added gesture icons to the Care Lenses screen to indicate how one could operate them (e.g., the button "Pain management" in Figure 2 also shows an icon for nodding to indicate users can activate it with this gesture, and the button "order pain scale" holds an icon for the tilting gesture to indicate that users can switch to it by tilting their head to the right).

Table 2. Gesture Set for the Head Gestures of Care Lenses (Icons from Care Lenses UI)

Gesture				
Description	Nodding	Tilting to the side	Shaking head	Turning to the side
Usage	Selecting, pushing button (approving)	Switching buttons / controls, setting values / scales	Cancelling, back to main	Back / forward in a workflow

4 The Study

4.1 Measurements Applied

To compare the two mechanisms, we counted user and mechanism-based errors. We did so by looking at a combined video stream that showed the participant interacting with the patient and the corresponding screen Care Lenses screen (see Figure 4). Regarding user errors, we counted the number of times participants did not know how to proceed (e.g., when they did not know which gesture to apply in a specific situation) and their duration. For mechanism-based errors, we counted the times a participant acted correctly but the lenses did not react correctly (e.g., nodding without the mechanism recognizing it), which often resulted in participants asking the researchers what to do (e.g., how to proceed) because they had expected the Care Lenses to react.

To shed light on the effort users needed to take in order to operate the Care Lenses, we applied the well-known (raw) task-load index (TLX) questionnaire (Hart & Staveland, 1988) and asked people to fill it in after each of the four tasks in the study. The TLX uses a scale from 0 to 20 to investigate a task's workload dimensions such as mental, physical, and temporal demands and perceptions about performance, effort, and frustration. Researchers have found the TLX questionnaire to provide a good and valid means to access and compare task load from tool support for human work in healthcare and many other domains (Hart, 2006; Hart & Staveland, 1988). As usual in many studies, we used the raw TLX questionnaire without individual weights.

Besides errors and task load, to answer our research question, we needed insights into the task performance resulting from the two mechanisms. Therefore, we timed how long users took to finish a task from the beginning (i.e., when users started the task manually) to the end (i.e., when they entered the final screen named "end" in Table 1). We also took the time that the participants spent on each step in the tasks based on when the system displayed the dialogue to them. In this way, we examined out how well each mechanism supported specific steps.

As we describe above, personal contact and empathy represent important aspects in providing care. Therefore, we analyzed the videos that we took during the study and coded them with different categories to capture these dimensions. We applied continuous codes (during the task, one code always remained active while we did not select the others) to depict whether the participants turned toward the patient. We coded whether the participant had turned their body towards the patient or not and whether the participant looked in the patient's direction or not. We used this factor to approximate whether the participant paid attention to the patient or not (cf. Mehrabian, 2017). As coded continuously, we counted how long each code lasted for. To measure personal contact more directly, we coded whether the participant talked (or did not talk) to the patient. However, note that, in contrast to turning to patients, different individuals talk to patients for different amounts of time as some caregivers may, for example, use more words or talk more slowly than others.

4.2 Course of the Study

We conducted the study with care providers from intensive care and home and elderly care. All participants noted they found pain management a relevant task. Table 3 shows the participants per provider.

The participants varied in age from 25 to older than 50. Further, 18 were female and six were male. The participants had 11.7 years of experience in care on average (SD = 7.8). Fifteen participants dealt with pain management regularly, and the other nine were familiar with it from nursing school. We looked for correlations between participants' demographics and the results we gained from the measurements we applied, but we did not find any medium or strong correlations. Thus, we assume that the participants' demographics did not have influence the results that we present below.

Table 3. Care Providers and Participants in the Study

Provider	Participants
Elderly care ward	6
Intensive care shared apartments	6
Care laboratory, participants from different care providers	4
Intensive care stationary unit, participants from different providers	8

To provide external validity, we conducted the study in empty patient rooms. Participants were care workers on duty during the time we conducted the study. The participants received permission to take a break from regular work and participate in the study. They wore their care uniform and carried around items they used in daily work (see Figure 4). However, our tasks differed from real care tasks mainly in that we did not work with real patients. One researcher took the patient role because we did not receive ethical approval from our national review board to test prototypes with real patients. While we obviously would have preferred to test the system with real patients (which we plan for later studies), with our setting, we could keep the patient's behavior constant (e.g., same answers to all participants the caregiver asked for pain levels). For all tasks, we asked the caregivers to follow guidelines they received on the Care Lenses even if they were used to a different procedure.

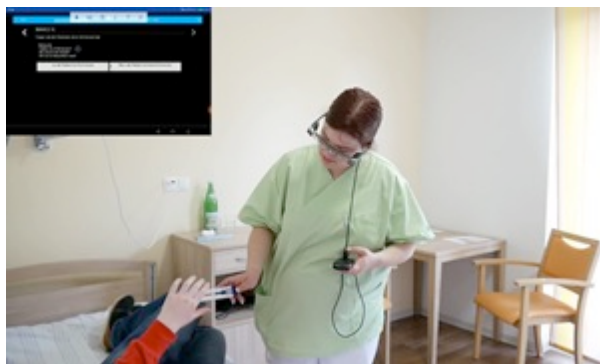


Figure 4. A Participant in the Study Handing Over the Pain Scale to the Patient and Care Lenses Screen

4.3 Study Design and Participants

We chose a counterbalanced within-subjects design to detect carry-over effects that arose from using either a mechanism first and to examine effects that familiarity with a task caused (i.e., whether the caregiver performed it for the first or second time). Half of the participants started by using the handheld device and then the gestures, and the other half started with gestures. We provided a brief tutorial to participants for the respective interaction mechanism. Besides providing the tutorial and briefly explaining the tasks, we also instructed participants to complete tasks according to the guidance of Care Lenses. We provided no other instructions. After we completed each task, we provided the participants with a TLX questionnaire. After they completed all tasks, we conducted an interview with the participants in which we asked them about how they perceived the two mechanisms they had tested and their general perceptions about the Care Lenses.

In the tutorial, users practiced each gesture briefly to ensure they could do them properly and to become familiar with the head movements. From this tutorial, they also became familiar with the icons that screens in the Care Lenses used to depict available gestures (see Figures 2 and 3). As we describe above, we implemented gestures to work on the spot. Therefore, we told participants to expect immediate reactions to gestures and to repeat a gesture if no reaction happened. We also told them that, in case of unexpected reactions, they could go back one step in a workflow (see the gestures in Table 2).

Note that, in our comparison, we clearly have bias towards the handheld device. People know about interacting with handheld touch devices well and, thus, likely found it more familiar. In contrast, they likely found the head gestures new and more difficult to use initially (cf. Plaumann et al., 2015). We could provide an extended training session for the gestures due to time restrictions in care organizations, and such training may not have diminished this gap fully anyway. As a consequence, we did not expect the head gestures to outperform the handheld device but aimed for at least comparable performance.

5 Results

5.1 Data Analysis

We analyzed data with SPSS. To analyze the TLX questionnaire, we used t-tests for paired samples as data had a normal distribution (Shapiro-Wilk test). The data for the usage and performance measurements did not have a normal distribution, so we used the Wilcoxon signed rank test for it. If we found significant differences between the mechanisms, we computed linear regression models to investigate causal effects.

We checked the inter-rater reliability of our codes for performance and interaction by calculating interclass correlation coefficients (<.8 for all codes). We had to exclude some measurements on usage and performance for both conditions. We did so when participants did not follow the guidance on the screen due to misunderstandings (which occurred especially when they conducted the task for the first time) or when a mechanism error occurred that caused them to restart the task when they had already completed it halfway or more (to ensure validity of comparisons). This way, the sample size changed 15 participants for these measures. However, the Wilcoxon signed rank test is robust against small sample sizes and our comparisons met all requirements for alpha-values of 0.05 and 0.01 (see values reported below).

5.2 Usability

In analyzing the data the mechanisms' usability, we found more user errors for the gesture condition compared to the handheld condition ($z = -2.634$, $p < .001$, $T = 8.0$, $n = 15$). We also found more mechanism-based problems for gestures ($z = -3.313$, $p < .001$, $T = 0$, $n = 15$) and longer periods in which participants asked for help ($z = -2.04$, $p < .05$, $T = 13.0$, $n = 15$) and received help ($z = -2.09$, $p < .05$, $T = 7.0$, $n = 15$). Table 4 overviews the corresponding values.

We found only a significant difference in mechanism-based problems if participants used gestures *before* handheld touch—if they used the handheld first (and, therefore, already knew the workflow), they produced much less errors in the following gesture condition. This finding suggests that the participants had more difficulties with the gestures if they did not know the task and therefore, that the sequence of conditions caused the overall significant difference.

Table 4. Results for Error Measures with Significant Differences (Wilcoxon Signed Rank Test)

Category	Handheld	Gestures
Average number of user errors	1.87	4.6
Average number of mechanism problems	.07	6.4
t (user asking) in sec	1.8	7.8
t (help provided) in sec	2.0	15.5

We can attribute the fact that participants produced far more errors when they used the gesture mechanism than the handheld mechanism to the mechanism's novelty for the participants, which may have caused errors such as their forgetting the correct gesture to process. In addition, we used a prototype, which sometimes did not recognize gestures correctly. As such, as Table 4 shows, people spent more time asking for help or receiving support (3.8 seconds on average for handheld, 23.3 seconds for gestures).

5.3 Task Load

Regarding task load, we found significant differences in physical demand ($t(24) = -2.594, p < .05$), effort ($t(24) = -2.179, p < .05$), and frustration ($t(24) = -2.905, p < .05$). As Table 5 shows, all values resided in the lower levels of demand in the TLX scale (3 to 7). Looking deeper into these figures, we found no significant differences for any item if participants used handheld touch before gestures. This finding means that, if participants knew the task in advance, gesture interaction did not provide significant extra load. The results for task load fit the results for usability in Section 5.2. The more user and mechanism-based errors that participants experienced may have caused the higher load for gesture interaction. Regarding the bias, we assumed that we would find as much (see Section 4.3).

Table 5. TLX Scores

TLX item	Handheld	Gestures
Mental demand*	1.56	3.44
Physical demand*	1.64	4.16
Temporal demand*	1.12	3.32
Effort *	.80	3.32
Overall performance*	1.64	3.6
Frustration	1.76	3.32

Results marked * differ significantly with a paired t-test ($p < .05$)

5.4 Performance during Tasks (Original Data)

Participants conducted and finished all tasks successfully. However, we found significant differences. For the whole task, the participants needed on average 141.3 seconds with the handheld device and 183.3 seconds using gestures.

Table 6. Average Times for Tasks

Step	t(handheld) in sec	t(gestures) in sec
5	17.3	38.6
Overall	141.3	183.3

All values differ significantly in a Wilcoxon signed rank test.

As Table 6 shows, we found a significant difference in the time that participants spent on step five ($z = -2.442, p < .05, T = 17, n = 15$). Analyzing the differences in task-execution times, we found two important aspects. First, significant time differences appeared when participants had to use the tilting gesture (see Table 2) to set a value on the pain scale (step five). When they did not use this gesture, we found no significant differences in performance. In addition, when participants used the tilting gesture repeatedly for the same task as in the loop between steps five and six (see Section 3.2), the difference in performance became much smaller, which suggests a learning effect for the gesture.

Second, the additional time that participants spent for tasks in the gesture condition included time for dealing with user and mechanism-based errors and for asking and receiving help as Table 4 shows. Thus, one should note that issues with using the mechanism and its proper functioning influenced participants' task-execution performance. However, this time also added to the overall time we compared and, therefore, may have superseded other effects. In fact, we found that the majority of additional time that participants spent arose due to their brief exposure to the gesture mechanism (e.g., when they forgot one of the gestures) or to technical issues (e.g., when they did not recognize gestures).

5.5 Performance after Data Cleaning

As we were interested in how well participants performed with the Care Glasses apart from the issues they experienced with the tilting gesture, we cleaned the data by removing the time that participants needed to resolve unwanted (technical) issues. We re-coded the data and added a code that indicated that people spent time with usage issues rather than the task they were supposed to do. We applied it when participants started to focus on difficulties with operating the lenses and until they resolved the issues and began

executing the task again. We then re-calculated the time they spent on the different tasks and steps in them and compared them again.

We show selected performance data after data cleaning in Table 7. Interestingly, we did not find any significant differences in overall task performance after cleaning. For sequences in which participants conducted the handheld condition before the gestures, we found that they executed the workflow more quickly with gestures (handheld average 152.6 seconds, gestures average 127.2 seconds, $z = -2.032$, $p < .05$, $T = 2.0$, $n = 7$). Further, in linear regression analysis, we found that the sequence of conditions (independent variable) had significant effects on task performance in handheld or gesture conditions (handheld: $R^2 = .297$, $F = 9.864$, $\beta = -.575$, $p < .01$; gestures: $R^2 = .458$, $F = 13.686$, $\beta = .703$, $p < .01$; residuals normally distributed in a Kolmogorov-Smirnov test). This finding suggests that, for the cleaned data, learning effects mainly caused the differences in performance when participants performed the task twice rather than the mechanism they used.

Table 7. Overall Task Performances in Both Sequences and with the Handheld Condition Done Before the Gesture Condition (L) and Personal Interaction for Different Sequences of Handheld and Gesture (R)

t(handheld)	t(gestures)	Interaction	t(handheld) in sec	t(gestures) in sec
Both sequences		Handheld before gestures		
135.9	147.6	Head/body tow. Patient*	67.2	21.3
Handheld before gestures*		Not talking to patient*	108.2	71
152.6	127.2	Gestures before handheld		
		Head/body tow. Patient*	18.5	31.3
		Not talking to patient*	76.1	123.4
Values marked * differed significantly in a Wilcoxon signed rank test ($p < .05$)				

5.6 Patient Interaction

For all participants and tasks, we did not find any significant differences in the interaction with patients. Looking at the different sequences of conditions provides better insights: if participants used the handheld before gestures, we found that, for handheld, the participants turned their body and head much longer to patients (handheld average 67.2 seconds, gestures average 21.3, $z = -2.197$, $p < .05$, $T = 1.0$, $n = 7$) but spent longer not talking to patients (handheld average 108.2 seconds, gestures average 71 seconds, $z = .2201$, $p < .05$, $T = 1.0$, $n = 7$) (see Table 6). The findings reversed with the opposite sequence: here, we found that participants who used gestures before the handheld looked longer at patients (handheld average 18.5 seconds, gestures average 31.3, $z = -2.1$, $p < .05$, $T = 3.0$, $n = 8$) but also spent longer not talking to patients (handheld average 76.1 seconds, gestures average 123.4 seconds, $z = -2.521$, $p < .05$, $T = 0$, $n = 8$).

Looking at this data, it seems that, despite the mechanism they used first, participants paid more attention to the patient but less verbal interaction with that mechanism compared to the second one). This effect could have arisen due to the sequence rather than the mechanisms: once participants were more familiar with the task and its support on the Care Lenses, they may have felt more comfortable when they used the Care Lenses for the second time for this workflow and, therefore, paid more attention to the patient. In the same way, the second time they conducted the task, they may have acted in a more routine and less explicit way to do the task, which caused them to talk less. Our regression analysis support this finding: we found that condition sequence (independent variable) had a significant effect on the attention that the participant paid to the patient for the handheld condition ($R^2 = .231$, $F = 7.325$, $\beta = -.518$, $p < .05$) and on not talking to the patient for both conditions (handheld: $R^2 = .312$, $F = 10.52$, $\beta = -.587$, $p < .01$; gestures: $R^2 = .329$, $F = 8.369$, $\beta = .612$, $p < .05$).

All residuals had an equal distribution in a Kolmogorov-Smirnov test, which suggests that the familiarity with the task proved decisive for differences in the interaction with the patient rather than the mechanism.

5.7 Perceptions of Care Lenses in Practice: Reactions of Caregivers

In the interviews we conducted after the participants completed all tasks, most provided positive feedback about the Care Lenses and their application in practice (see Janßen & Prilla, 2019). Statements included the wish to use Care Lenses in practice (“I would wish that the Care Lenses will arrive in practice!”) and the availability of information during care (“For assessment I think it is great that I can directly access it at the patient”). Despite these positive statements, the caregivers also stated concerns about how Care Lenses might change care (“[I could] look into the Care Lenses without focusing on the patient because in care patients expect caregivers to talk with them”) or on putting too much responsibility to the glasses (“Perhaps one relies too much on the device without rechecking”). Especially when it came to how patients perceived the Care Lenses, some participants expressed concern. They said that patients “do not take them seriously” when wearing Care Lenses or that “patients suffering from dementia could be even more irritated by Care Lenses than they usually are, which is a big problem for them”. However, others also mentioned that “later generations of patient will possibly not have this problem” and that patients would “accept the Care Lenses if they get a proper explanation” (for more statements, see Janßen & Prilla, 2019).

Besides these general comments on the acceptance and applicability of Care Lenses in practice, the participants also commented on the two mechanisms’ advantages and disadvantages. For example, two caregivers stated that they saw a speed advantage in using gestures while executing workflows on Care Lenses in that using the touchpad they “need to point and click”, while performing gestures always “triggers a certain function directly”. On top of that, three caregivers mentioned one has to look onto the touchpad in order to use it, which requires “time” and “concentration”. Another participant noted the gestures’ naturalness as a benefit since it allowed one “to control Care Lenses naturally while talking with patients” without them even noticing it. On the other side, five caregivers stated they saw speed disadvantages in using the gestures in that the gestures were more error prone, which led to their feeling slowed down. This feedback concurs with the bias we describe above and with our findings from our analysis, and we can explain them due to our having used a prototype. Further, another explanation for the speed disadvantage lies in the fact that users would have to concentrate more on “which gesture should be used for what”, which could cause stress and concurs with the higher number of user errors that we report in Section 5.2. According to caregivers, they noted that touchpads have a benefit in that anyone can use them, while people with health problems at the neck could possibly not use gestures. Overall, most participants mentioned the “hands-free advantage in using gestures. Several participants concluded that “gestures are the better control at the patient” and that the touchpad should be used either “at the beginning” for getting used to Care Lenses or for tasks “away from patients”.

5.8 Summary of the Results

Our results show that participants encountered many more errors with the gesture mechanism than the handheld mechanism, which also resulted in better TLX scores for the handheld mechanism. However, these errors likely arose due to the mechanism’s prototype status, the tilting gesture that caused problems for some participants, and the difference in familiarity between the two mechanisms. Indeed, we found that the mechanism did not have any main effects in and of itself; rather, we found only sequence and familiarity with the workflow had an effect. Participants’ statements in the final interview highlight some of the gesture mechanism’s advantages and its applicability to practice.

6 Discussion

6.1 Hands-free Support in Care via Head Gestures: Does it Work?

In our research question, we ask to what extent head gestures could make hands-free AR support applicable in care practice. As an answer to this question, we can state that, despite the bias for the more familiar touchpad interaction, our head gestures often worked equally well. Participants could use gestures intuitively and recognize them reliably, which concurs with related work from other domains (Azimi et al., 2018; Garrett et al., 2015; Sharma et al., 2018; Yi et al., 2016). In other words, we compared a familiar with a novel interaction mechanism and found that the novel mechanism did not perform that much worse in the worst case and better in the best case. Indeed, participants’ statements noted as much. Therefore, we can conclude that head gestures represent a promising way to provide hands-free AR support in care. However, our findings also show that we still need to deal with some remaining issues. Among them, we found that some head gestures created difficulties for users and that the gesture mechanism created more task load

than the handheld. Therefore, we have much work to do until we can use this interaction mechanism to provide hands-free AR interaction in care. In subsequent sections, we discuss our results.

6.2 The Impact of Familiarity with Care Procedures and Interaction Mechanisms

In the analysis, we often found that the handheld mechanism's apparent advantages such as faster execution for certain steps or less task load only occurred if participants used the head gestures before the handheld. In this reverse sequence (handheld before gestures), participants already knew the task from the handheld condition, and it seems that this knowledge made using the gestures easier or at least did not amplify problems that resulted from the new interaction mechanism (as in the case of using gestures first). On the other hand, if participants did not know both the workflow and the (gesture) interaction, their performance decreased. Thus, we can conclude that, with more familiarity with the workflow support in the Care Lenses, gesture interaction can provide equal (or even a better means) of interacting with AR assistance in care. Further, not knowing the exact procedure likely amplified perceived and measurable difficulties with the interaction mechanism. In practice, this effect would most likely certainly diminish over time as our findings on performance and other factors (cases in which participants used gestures after the handheld) show. The participants' statements also show that gestures can be helpful when interacting with and caring for the patient. Thus, we conclude that the head gestures can constitute a good means to control AR support for care tasks after one becomes familiar with it (as it is the case for most interaction mechanisms). However, some challenges remain, which we discuss in Section 6.3.

6.3 Gesture Support is only as Good as its Worst Gesture: Tilting Gesture

The number of errors and the differences in TLX scores (though residing on good to acceptable levels) show that participants found the gesture mechanism more difficult to use than the handheld mechanism. Our participants faced a significant challenge with the tilting gestures to switch buttons or set values. Whenever they used it (and only in these cases), they performed significantly worse in the respective step. After we cleaned the data in which we removed sequences in which the participants spent time with asking for and receiving our help, this difference no longer appeared to that extent. This finding suggests that, as a gesture, tilting the head lacks intuitiveness or that people find it much more difficult to perform correctly, which lowers the mechanism's usability and likely increases task load. We conclude from this finding that gestures can be a proper mechanism for hands-free interaction with AR in care as long as one provides users with an easy-to-operate and semantically intuitive gesture set. Note, however, that the issues some users had with using the tilting gesture did not lead to negative perceptions on task load or frustration as the TLX scores show (frustration scored 3.32 on average, a very low score, and it is the only aspect in which the TLX score for the gestures was not significantly higher than for the handheld).

While we will spend further work on making the tilting gesture easier for users, replacing it may also be a way to proceed. However, no semantically fitting head gesture remains in the body of head gestures that people commonly use: researchers have found moving the head up and down too close to nodding and head movements to *draw* gestures too difficult in practice (Yi et al., 2016). Thus, we may find solutions in mixed modalities or interfaces specifically for hands-free interaction, which we discuss in Section 6.4.

6.4 Future Work: Mixed Modalities and Designing for Hands-free Interaction

Our study suggests that simple head gestures such as nodding and turning the head to the side have the potential to help caregivers conduct care tasks. They worked smoothly in our study and (after we eliminated delays caused by user and mechanism errors) even outperformed handheld touch interaction in certain situations. As we mention above, we also found limits to this support when it came to more complex gestures such as the tilting gesture that we used for switching between options and values. A good solution may include a mixed modalities approach that combines head gestures and speech input. Such an approach could use the best of both mechanisms: it keeps subtle and easy-to-perform head gestures as the main control mechanism (e.g., choosing buttons) and adds speech input for speech commands such as entering numbers (e.g., the pain level that a patient selects as Figure 3 show). In contrast to control commands, patients may understand why the caregiver says a certain number into a device if it matches the number they provide on the scale.

Using a mixed modalities approach, however, does not completely solve the issues we found. It does not solve selection problems such as switching to another branch of a workflow (e.g., stating the patient is not in pain as Figure 3 shows), and voice input may become clumsy when one needs to enter complex values

(including complex numbers and units). Therefore, besides mixed modalities, we may strive to design specifically for hands-free interaction and control with head gestures. First, we could design the user interface for hands-free interaction and, thus, without multiple buttons to choose from. Rather than such buttons, head gesture control can work much better if one can make only one choice to approve or to dismiss. For our case, such an interface means that the pain-management workflow that the user selects after context detection (see Figure 2) could change: the interface would provide only one button that offered to start the pain management workflow. Switching to the ordering workflow would then mean that the user would dismiss this option by shaking their head, which would bring up a button to start the ordering process as a second option that the user could approve via nodding. This procedure would work for all steps that we discuss in this paper. To implement it, we would need better context recognition to narrow down choices to a manageable number and a system of prioritizing options. For the latter, we could prioritize options with patient interactions to make them accessible first. In tasks without this interaction, shaking the head once or twice may not be a huge problem and still lead to good task support quickly. Second, image and object recognition may enable the Care Lenses to semi-automatically enter numbers displayed on devices or on the pain scale that the patient manipulated, which would mean users had to only approve or dismiss the value read in automatically. Our early work on this approach has shown promise

6.5 Sharing Care Work: The Care Lenses as Enabler for Informal Caregivers?

Our results show that caregivers can use the Care Lenses without considerable cognitive or other load while providing care for a patient. As such, it could also be applicable for reinsuring and guiding informal caregivers and for *sharing* the care work between professional and informal caregivers. Of course, due to both ethical and legal constraints, one must not use the Care Lenses to allow untrained caregivers to conduct care.

Rather than that, informal caregivers could use the Care Lenses to ensure they provide care correctly after being trained to do so. Many researchers and professionals see such training as necessary (e.g., González-Fraile et al., 2015; Phillips et al., 2016) due to the reasons that we mention in Section 1. If used for these purposes, informal and professional caregivers may also use Care Lenses to adapt care workflows to patients' needs or to plan their cooperation in care tasks (e.g., see Wittenberg, Kwekkeboom, Staaks, Verhoeff, & de Boer, 2018). In addition, informal and formal caregivers could use the Care Lenses to share information on treatment and care tasks in order to increase security and cooperation (cf. Chimowitz, Gerard, Fossa, Bourgeois, & Bell, 2018).

6.6 Impact on New (Business) Models of Care and Care Organizations

While we do not primarily focus on a certain business case for care in this paper, our work forms one part of a larger research stream that focuses on providing a concept to use AR to support care. In practice, the Care Lenses ideally save time (to access documentation, to ask for help, to look up a procedure), increase care quality (by adhering to standards, better documentation, and expert help), and enable informal caregivers to become a more active and informed part of the local care system (by knowing what professional caregivers do and did, by receiving guidance in the care tasks they were trained for, by cooperating with professional caregivers on care for the respective patient). Accordingly, the technology would not only provide benefits for caregivers (relieve from pressures) and patients (care and life quality) but also enable care providers to deliver good care for all patients in times in which it becomes more and more difficult in many Western and Asian societies. Of course, Care Lenses does not constitute *the* solution for all problems in care, but it does contribute to IT-supported care.

In this study, we focus on developing and evaluating an AR-based interaction mechanism that enables professional and informal caregivers to tap from its potential benefits. We show that the head gestures enabled AR to potentially benefit nurses in care work such as receiving information while providing care with their hands and body. Therefore, the mechanism also enables care providers, hospitals, and other organizations involved in care to put the Care Lenses into practice and make them a part of the IT-supported care.

6.7 Limitations

We ran our study in a realistic setting but without real patients. We did not use real patients due to ethical reasons and the study's setting since we wanted the patients to behave in a certain way to control the study. As such, we do not consider patients' perspectives on and perceptions about AR devices in care. We asked

the caregivers who participated in the study about the feedback patients might give, and they provided quite different feedback, which indicates that, with proper explanation, patients could accept the Care Lenses. However, beyond this feedback, it remains to see how patients react to the Care Lenses and how they react to our gesture mechanism. As we indicate elsewhere in the paper, we plan to evaluate the Care Lenses with real patients.

In our study, we compare head gestures (a novel interaction mechanism) with touch-based interaction (a well-known interaction mechanism). We recognize that we leave out many other modalities such as speech-based interaction and touch interaction on the device's frame, which we left out for reasons such as hygiene and user constraints. In addition, we did not compare AR-based support to support provided on paper as it seems obvious that receiving information during care has advantages over interrupting care and going back to paper. However, for all alternative modalities and ways to become informed during care, the need to scrutinize the Care Lenses' advantages to show which benefits it can provide for care remains.

To choose gestures to use for the study, we considered head movements that people intuitively make and the related literature. Of course, we recognize that we used Western European and American-centric gestures and that people in other places in the world use and interpret gestures differently. Therefore, our results primarily apply to Western Europe and the US. We believe that one can develop gesture sets for other cultural areas as well.

Finally, we conducted the study with a sample of caregivers that—despite representing the care sector in Germany—was small. Researchers could extend our sample size in further work to add to our results' the generalizability. In addition, the task used did not go beyond medium complexity, a choice we made deliberately to not include too much complexity and burden on the participants (a very complex process and a new mechanism).

7 Conclusion

In this paper, we present and explore head gestures as a means for people to interact with AR support for care tasks without their hands. The need for such support arises from the complexity and quality affordances in care work and the need for caregivers to use one or both their hands to conduct care tasks. We found that our head gestures performed equally well in many situations when compared to handheld touch controls, which we used as a baseline. As such, we conclude that head gestures can be a means for hands-free AR control in care work. We also show and discuss our mechanism's shortcomings and open issues for using head gestures in care work. Finally, we present potential ways to deal with these issues while keeping head gestures as the main interaction mechanism of the Care Lenses. We plan further work to implement and evaluate these improvements.

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References

- Ackerman, M. S., Büyüktür, A. G., Hung, P.-Y., Meade, M. A., & Newman, M. W. (2018a). Socio-technical design for the care of people with spinal cord injuries. In M. S. Ackerman, S. P. Goggins, T. Herrmann, M. Prilla, & C. Stary (Eds.), *Designing healthcare that works*. New York, NY: Elsevier.
- Ackerman, M. S., Goggins, S., Herrmann, T., Prilla, M., & Stary, C. (2018b). *Designing healthcare that works*. New York, NY: Elsevier.
- Aldaz, G., Shluzas, L. A., Pickham, D., Eris, O., Sadler, J., Joshi, S., & Leifer, L. (2015). Hands-free image capture, data tagging and transfer using Google Glass: A pilot study for improved wound care management. *PloS One*, *10*(4), e0121179.
- Amsha, K. A., & Lewkowicz, M. (2015). CARE: An application to support the collective management of patients at home. In *Proceedings of the International Conference on Computational Science and Computational Intelligence*.
- Azimi, E., Winkler, A., Tucker, E., Qian, L., Sharma, M., Doswell, J., Navab, N., & Kazanzides, P. (2018). Evaluation of optical see-through head-mounted displays in training for critical care and trauma. In *Proceedings of the Conference on Virtual Reality and 3D User Interfaces*.
- Azuma, R. T. (1997). A survey of augmented reality. *Presence*, *6*(4), 355-385.
- Bossen, C. (2018). Socio-technical betwixtness: Design rationales for health care IT. In M. S. Ackerman, S. P. Goggins, T. Herrmann, M. Prilla, & C. Stary (Eds.), *Designing healthcare that works*. New York, NY: Elsevier.
- Bratteteig, T., & Wagner, I. (2013). Moving healthcare to the home: The work to make homecare work. In *Proceedings of the 13th European Conference on Computer Supported Cooperative Work* (pp. 143-162).
- Büttner, S., Mucha, H., Funk, M., Kosch, T., Aehnelt, M., Robert, S., & Röcker, C. (2017). The design space of augmented and virtual reality applications for assistive environments in manufacturing: A visual approach. In *Proceedings of the 10th International Conference on Pervasive Technologies Related to Assistive Environments* (pp. 433-440).
- Chimowitz, H., Gerard, M., Fossa, A., Bourgeois, F., & Bell, S. K. (2018). Empowering informal caregivers with health information: OpenNotes as a safety strategy. *The Joint Commission Journal on Quality and Patient Safety*, *44*(3), 130-136.
- Crossan, A., McGill, M., Brewster, S., & Murray-Smith, R. (2009). Head tilting for interaction in mobile contexts. In *Proceedings of the 11th International Conference on Human-Computer Interaction with Mobile Devices and Services*.
- Datcu, D., Lukosch, S. G., & Lukosch, H. K. (2016). Handheld augmented reality for distributed collaborative crime scene investigation. In *Proceedings of the 19th International Conference on Supporting Group Work* (pp. 267-276).
- Esteves, A., Verweij, D., Suraiya, L., Islam, R., Lee, Y., & Oakley, I. (2017). SmoothMoves: Smooth pursuits head movements for augmented reality. In *Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology* (pp. 167-178).
- Fakourfar, O., Ta, K., Tang, R., Bateman, S., & Tang, A. (2016). Stabilized annotations for mobile remote assistance. In *Proceedings of the Conference on Human Factors in Computing Systems* (pp. 1548-1560).
- Garrett, B. M., Jackson, C., & Wilson, B. (2015). Augmented reality m-learning to enhance nursing skills acquisition in the clinical skills laboratory. *Interactive Technology and Smart Education*, *12*(4), 298-314.
- González-Fraile, E., Solà, I., Ballesteros, J., Rueda, J.-R., Martínez, G., & Santos, B. (2015). Information, support and training for informal caregivers of people with dementia. *Cochrane Database of Systematic Reviews*. Retrieved from <https://www.cochranelibrary.com/cdsr/doi/10.1002/14651858.CD006440.pub2/full>

- Güldenpfennig, F., Nunes, F., & Fitzpatrick, G. (2015). ProxyCare: Integrating informal care into formal settings. In *Proceedings of the 9th International Conference on Pervasive Computing Technologies for Healthcare* (pp. 141-144).
- Hart, S. G. (2006). NASA-Task Load Index (NASA-TLX); 20 years later. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 50(9), 904-908.
- Hart, S. G., & Staveland, L. E. (1988). *Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research*. Retrieved from <http://humansystems.arc.nasa.gov/groups/TLX/downloads/NASA-TLXChapter.pdf>
- Janßen, M., & Prilla, M. (2019). Usability and utility of head mounted displays in care according to caregivers. In *Proceedings of the 7th International Conference on Infrastructures for Healthcare*.
- Jia, P., Hu, H. H., Lu, T., & Yuan, K. (2007). Head gesture recognition for hands-free control of an intelligent wheelchair. *Industrial Robot: An International Journal*, 34(1), 60-68.
- Johnson, S., Gibson, M., & Mutlu, B. (2015). Handheld or handsfree? Remote collaboration via lightweight head-mounted displays and handheld devices. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing* (pp. 1825-1836).
- Kobayashi, L., Zhang, X. C., Collins, S. A., Karim, N., & Merck, D. L. (2018). Exploratory application of augmented reality/mixed reality devices for acute care procedure training. *Western Journal of Emergency Medicine*, 19(1), 158-164.
- Ku, P.-S., Wu, T.-Y., & Chen, M. Y. (2017). EyeExpression: Exploring the use of eye expressions as hands-free input for virtual and augmented reality devices. In *Proceedings of the 23rd ACM Symposium on Virtual Reality Software and Technology*.
- Kytö, M., Ens, B., Piumsomboon, T., Lee, G. A., & Billinghamurst, M. (2018). Pinpointing: Precise head- and eye-based target selection for augmented reality. In *Proceedings of the Conference on Human Factors in Computing Systems*.
- Lee, J.-Y., Song, Y. A., Jung, J. Y., Kim, H. J., Kim, B. R., Do, H.-K., & Lim, J.-Y. (2018). Nurses' needs for care robots in integrated nursing care services. *Journal of Advanced Nursing*, 74(9), 2094-2105.
- Mather, C., Barnett, T., Broucek, V., Saunders, A., Grattidge, D., & Huang, W. (2017). Helping hands: Using augmented reality to provide remote guidance to health professionals. *Studies in Health Technology and Informatics*, 241, 57-62.
- Matthies, D. J., Haescher, M., Alm, R., & Urban, B. (2015). Properties of a peripheral head-mounted display (PHMD). In *Proceedings of the International Conference on Human-Computer Interaction* (pp. 208-213).
- Mehrabian, A. (2017). *Nonverbal communication*. New York, NY: Routledge.
- Milgram, P., & Kishino, F. (1994). A taxonomy of mixed reality visual displays. *IEICE Transactions on Information and Systems*, 77(12), 1321-1329.
- Morency, L.-P., Sidner, C., Lee, C., & Darrell, T. (2007). Head gestures for perceptual interfaces: The role of context in improving recognition. *Artificial Intelligence*, 171(8-9), 568-585.
- Phillips, S. S., Ragas, D. M., Tom, L. S., Hajjar, N., Dong, X., & Simon, M. A. (2016). Voices of Informal caregivers and community stakeholders: Whether and how to develop an informal caregiver training program. *Journal of Community Health*, 41(3), 550-556.
- Plaumann, K., Ehlers, J., Geiselhart, F., Yuras, G., Huckauf, A., & Rukzio, E. (2015). Better than you think: Head gestures for mid air input. In *Proceedings of the IFIP Conference on Human-Computer Interaction* (pp. 526-533).
- Poulsen, A., & Burmeister, O. K. (2019). Overcoming carer shortages with care robots: Dynamic value trade-offs in run-time. *Australasian Journal of Information Systems*, 23, 1-18.
- Preuveneers, D. (2015). The GhostHands UX: Telementoring with hands-on augmented reality instruction. In *Proceedings of the 11th International Conference on Intelligent Environments*.

- Ruban, T., & Wood, J. (2016). *Recognizing head gestures for head-mounted displays*. Retrieved from http://stanford.edu/class/ee267/Spring2016/report_ruban_wood.pdf
- Rudigkeit, N., Gebhard, M., & Gräser, A. (2014). Towards a user-friendly AHRS-based human-machine interface for a semi-autonomous robot. In *Proceedings of the International Conference on Intelligent Robots and Systems*.
- Schmalstieg, D., & Hollerer, T. (2016). *Augmented reality: Principles and practice*. Boston, MA: Addison Wesley.
- Schorch, M., Wan, L., Randall, D. W., & Wulf, V. (2016). Designing for those who are overlooked: Insider perspectives on care practices and cooperative work of elderly informal caregivers. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (pp. 787-799).
- Sharma, M., Ahmetovic, D., Jeni, L. A., & Kitani, K. M. (2018). Recognizing Visual Signatures of Spontaneous Head Gestures. In *Proceedings of the Winter Conference on Applications of Computer Vision* (pp. 400-408).
- Siebert, J. N., Ehrler, F., Gervaix, A., Haddad, K., Lacroix, L., Schrurs, P., Sahin, A., Lovis, C., & Manzano, S. (2017). Adherence to AHA guidelines when adapted for augmented reality glasses for assisted pediatric cardiopulmonary resuscitation: A randomized controlled trial. *Journal of Medical Internet Research*, 19(5), e183.
- Starnes, T. (2013). Project glass: An extension of the self. *IEEE Pervasive Computing*, 12(2), 14-16.
- Terven, J. R., Raducanu, B., Meza-de-Luna, M. E., & Salas, J. (2016). Head-gestures mirroring detection in dyadic social interactions with computer vision-based wearable devices. *Neurocomputing*, 175, 866-876.
- Wittenberg, Y., Kwekkeboom, R., Staaks, J., Verhoeff, A., & de Boer, A. (2018). Informal caregivers' views on the division of responsibilities between themselves and professionals: A scoping review. *Health & Social Care in the Community*, 26(4), e460-e473.
- Wüller, H., Behrens, J., Garthaus, M., Marquard, S., & Remmers, H. (2019). A scoping review of augmented reality in nursing. *BMC Nursing*, 18, 1-11.
- Yi, S., Qin, Z., Novak, E., Yin, Y., & Li, Q. (2016). Glassgesture: Exploring head gesture interface of smart glasses. In *Proceedings of the 35th Annual IEEE International Conference on Computer Communications*.
- Zarit, S. H., Pearlin, L. I., & Schaie, K. W. (2019). *Caregiving systems: Informal and formal helpers*. New York, NY: Routledge.
- Zhu, E., Hadadgar, A., Masiello, I., & Zary, N. (2014). Augmented reality in healthcare education: An integrative review. *PeerJ*, 2, e469-e469.

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Michael Prilla is a professor for “Human-Centered Information Systems“ at Clausthal University for Technology. He works on the design of human computer interaction with a focus on supporting individual and cooperative work in domains and areas like healthcare, social work, learning and digitization. He understands the combination of information technology and human work and learning as socio-technical systems and used participatory approaches to aid the design and establishment of these systems. Prof. Prilla has written more than 110 publications in journals, conferences and books, and he is a member of the steering committee of German HCI (Fachbereich „Mensch-Computer-Interaktion“, Gesellschaft für Informatik). His current work is focused on the potentials of Augmented Reality for work and learning.

Marc Janßen is a PhD student and research assistant at Human Centered Information Systems of TU Clausthal. In project “Pflegebrille” he is responsible for the design of support and its user centered evaluation. He is particularly interested in possibilities for end users to influence or adapt the support provided by Augmented Reality for their work and learning. With his research he wants to investigate the advantages of Augmented Reality in care and its adaptation to the needs of caregivers in order to contribute to the establishment of Augmented Reality in everyday life.

Timo Kunzendorff is a PhD student and research assistant at Human Centered Information Systems of TU Clausthal. He works on the development and evaluation of project “Pflegebrille“. His interests are in supporting medical staff in their work and learning by Augmented Reality.

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