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Relating Factors for Acceptance of Health Care Technology: Focus on Mental Workload

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Abstract

Medical information systems and care robots are two typical examples of human computer interaction in health care. Although used in a stressful environment, effects on mental workload and acceptance are hardly evaluated. We conducted an experimental design including collaborative robotics and eye tracking in a nursing situation to test the practicability and plausibility of eye tracking as a measuring method for workload. Results showed that eye tracking is feasible if context factors are adjusted. Data reduction and classification of tasks are necessary.

Keywords:

Workload, Eye Movements, Health Information Systems

Introduction

Health information system (HIS) has already become an important part of daily health care. Investigations of usability of HIS often focus on technical issues and not on the whole system (technical, human). Interacting with a computer while operating daily working tasks means to switch attention between patients, computer and other competing tasks. This can lead to a high workload. Comparable to the use of HIS in medical settings are Human Robot Interactions (HRI) in health care: care assistance robots have the potential to compensate gaps in patient-centered care caused by demographic change [1]. The topic of HRI poses the challenge of safety issues as well as usability and acceptance by users. Meanwhile, physical limits in interaction with robots are well defined, there remain open questions – as well as in the topic of HIS - regarding mental issues like stress and strain and acceptance by users [2]. Working and interacting with a robot or a HIS for a whole working shift needs a high amount of attention. As a result, the workload can be too high to manage all competing tasks.

"Workload is defined as the physical and/or mental requirements associated with a task or combination of tasks" and "refers to that portion of the operators limited capacity actually required to perform a particular task" [3]. Accordingly, mental workload (MWL) may be an imbalance of resources of the operator and requirements of the task influencing the operator's performance. O'Donnell & Eggemeier addressed the lack of valid, objective measurement methods regarding psychophysiological correlates that can be applied in real work situations [4]. Advantages of psychophysiological methods are that they are uncontrollable and unmodifiable by the proband as well as spontaneously in response to stimuli. They can be an effective approach for workload analysis in a highly demanding work situation like a health care situation [5].

One aspect of analysing HIS is the integration of physiological (MWL) and intentional measures (for example, acceptance) [6]. For analysing "acceptance", there exist several models, e.g. the *unified theory of acceptance and the use of technology* (UTAUT) identifying four key factors (performance expectancy, effort expectancy, social influence and facilitating conditions) and four moderators (age, gender, experience and voluntariness) [7]. Several studies investigated mostly one or two of the factors, but only a few studies showed extensions as including individual characteristics to the UTAUT model. Leaving out individual characteristics is one of the main criticism of the UTAUT model as well as in health care research [8]. We propose MWL as an additional factor to the UTAUT model that influences behavioral intention.

As MWL is determined by task complexity and difficulty, it is probably a good predictor to explain the high amount of stress of health care staff [9]. Work psychology states that mental stress emerges of strain resulting from task requirements [10]. Knowing about a lack of acceptance of new technologies in health care – especially HIS – leads us to further hypotheses. Our main objectives are to validate eye movements as well as pupil width as physiological correlates for MWL measurements in health care settings to be able to test possible extensions of the UTAUT model.

Methods

Embedded in a students project, we developed an experimental simulation design. We used a simulated hospital room that holds environmental conditions stable (noise, lights). It contains a nursing bed, an over-bed table, a collaborative robot, a flatscreen TV as well as decoration equipment to make the hospital situation more realistic to the probands. Sirens and other hospital sounds are played for a more realistic scenario. The patient sits in bed with the over-bed table beside his right side, the collaborative robot is placed behind the table. The executing task of the robot is to handle the patient medication, something to drink as well as something to eat. The robot puts the three different objects on the over-bed table one after another and puts it back afterwards. The patient needs to lift up the objects in the time between and before the robot takes the object back 30 seconds later. There's a planned pause in HRI when the patient tries to solve a Sudoku. The described procedure is repeated twice; at the end of the setting, the proband is asked to fill out an adapted UTAUT questionnaire. The setting (without the UTAUT questionnaire) takes about 10 minutes. As the experimental setting – as well as real nursing settings – is complex and cannot be interrupted for standard subjective measurement methods, we use the eye tracking method for measuring cognitive parameters. We propose the use of mobile *pupil labs* binocular glasses that include two infrared (IR) spectrum eye cameras for dark pupil detection and a scene camera. The mobile using solution makes the pupil labs glasses very flexible as well as the very low weight of 37gr which supports the flexible research setting.

Additionally to physiological measures of workload, we use an adapted form of the UTAUT questionnaire including some questions addressing MWL and leaving out questions not matching to our research question. We already conducted pre-tests, each execution with another proband. The planned sample size is a minimum number of 90 probands, divided into two groups considering differences between "digital natives" and people over the age of 40.

Results

The first pre-tests – conducted by a group of students – showed the practicability of the study design and the potential of the method of eye tracking to measure MWL during a high demanding task situation. The pupil labs glasses only weigh around 37 grams and as reported by probands are well suited and pleasant to wear for a long time (around 15min). Wearing the eye tracker reportedly does not disturb the visual field of the proband, nor do the wires that are connecting it to the mobile phone. Those parameters ensure that the probands in this stationary – but as well as probands in more flexible – study designs are not extra loaded by the eye tracker. We asked our pre-test probands if the simulated area the experiment is performed in, felt like a realistic scenario for them. As one main goal of our study is to test eye tracking on its plausibility and practicability in a real nursing setting, it was important to create a realistic scenario. We optimized some objects concerning critic points the probands pointed out, like adding more hospital associated decoration to the walls.

Measuring stress via eye tracking in the first step means extracting data concerning pupil width. As we wanted do define MWL in interaction with technology (in this case: human robot interaction), we focus on extracting pupil width data at timestamps that refer to the collaboration of the proband and the collaborative robot. First data analyses within the pupil labs software resulted in a great amount of data as the world camera produces additional data. The results in the test setting are promising as parameters of pupil width and fixation were recognized correctly and could be correlated to specific situations in a qualitative manner. As Pupil Capture ejects a gaze map directly after recording, we could already point out that fixations on the robot took much longer than needed actually. While the robot already paused, the probands still fixated his arm.

While it does not seem reasonable to assess results to our UTAUT questionnaire with only n = 3 probands, we asked our probands about comprehensibility and content-related relevance.; we changed the wording of some questions to improve critical aspects

Discussion

We discussed possible extensions of the UTAUT model and identified first hints for MWL as a possible predictor to influence acceptance of new supporting technologies used in health care settings (MIS and Robots). This study demonstrated that it is feasible to use eye tracking in a real setting as glasses are small and lightweight. The investigation of an experimental setting including a collaborative robot seems to be a good starting point for testing our hypotheses in a protected realistic – but laboratory setting. Our goal was to validate whether the eye tracking method can be transferred to similar settings, we see some first results.

Nevertheless, there are some limitations which are relevant to consider. In the current setting we worked with inexperienced students, there was less equipment (i.e. medical records, information systems) and fewer sources which attracted attention (i.e. no interaction with other colleagues). Although the simulation is as close as possible to a real scenario, we expect more distraction in a real clinical setting. Therefore, our results may be less transferable.

Conclusions

We conducted a first pre-test for the eye tracking method as a valid measurement method for measuring MWL. While first pre-tests showed some promising hints for further studies, we identified the need for reducing relevant data as well as the need for another method measuring MWL to correlate the matching parameters.

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