Analysis of a Workload in Healthcare through a Simulation Experiment and Data Acquisition by Wearable Devices

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Abstract

In the healthcare field, workload management is important because the workload of healthcare professionals such as nurses affects the safety and quality of treatment and care for patients. However, changing circumstances surrounding operations are inevitable in healthcare, and workloads change from time to time in response to changing circumstances. Therefore, management is required to accommodate such changes. For this purpose, it is necessary to predict the workload in real time based on various factors such as the state of workers under changing conditions and reflect this in management, but no method has been established to predict the workload in healthcare in real time in response to changing conditions. Therefore, in this study, focusing on the development of Internet of Things (IoT) technologies, we conducted a simulation experiment in a simulated ward environment and acquired data that could be acquired by wearable devices available in real time to analyze the workload change during tasks. Several indicators showed a significant main effect on workload ($p < 0.01$), suggesting that multiple indicators of patient and ward conditions can be obtained in real time are effective in the evaluation of workload.

Keywords
Human factors, Workload management, Wearable device, and Simulation experiment.

1. Introduction

1.1 Background

Socio-technical systems require stable and high-quality services. In the healthcare field, safety problems have been reported as a result of the increased workload of healthcare professionals such as nurses, including errors of slips and lapses (Sutherland et al., 2019). Thus, the workload in healthcare affects the safety and quality of treatment and care for patients, and it has traditionally been the subject of management in the healthcare field. Traditionally, it has been proposed to adjust nurse staffing based on the number of patients in a ward, patient characteristics, and other factors as a discrete workload management for relatively long periods of time, such as each shift of a day (Sir et al., 2015; Huggins and Claudio, 2019). However, changing circumstances surrounding operations are inevitable in healthcare, and workloads change from time to time in response to changing circumstances. Therefore, management is required to accommodate such changes.

On the other hand, data acquisition using wearable devices and Internet of Things (IoT) technology has been developing in recent years. In the healthcare field, these technologies are being used to manage and utilize medical data. For example, monitoring the patient's condition and predicting the patient's risk of mortality has been under consideration (Davoudi et al., 2019; Aczon et al., 2021; Šabić et al., 2021). In addition, the promotion of database management of electronic medical records (Pollard et al., 2018) and the centralization of information through patient monitoring systems (Archip et al., 2016; Nahar, et al., 2020) have been considered to assist healthcare professionals. However, the use of data of healthcare professionals has not been developed, and there is still room for its utilization.

1.2 Objectives

In this study, we examine the use of data of healthcare professionals from the perspective of workload management. As abovementioned, changing circumstances surrounding operations are inevitable in healthcare, so it is necessary to predict the workload in real time based on various factors such as the state of workers under changing conditions and reflect this in management. However, no method has been established to predict the workload in healthcare in real time in response to changing conditions. Therefore, in this study, we conducted a simulation experiment in a simulated ward environment and acquired data that could be acquired by wearable devices available in real time. We analyzed the workload variation based on experimentally acquired data aiming at applying for measuring and visualizing workload in real time.

2. Methods

2.1 Experimental Outline

To acquire the data of workload analysis, we constructed an environment that simulated an actual medical practice and conducted a simulation experiment in which five participants performed treatment and care tasks in an

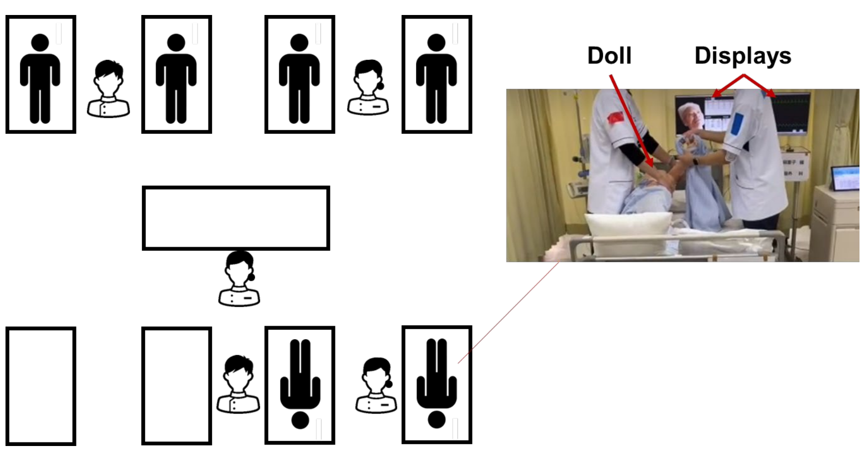

Figure 1. Overview of environment and simulator set up in the experiment

environment simulating a ward with up to eight beds for two hours. Figure 1 shows the overview of the constructed experimental environment.

The patient simulator consisted of dolls (Resusci Anne, Laerdal Medical Corp.) and 24-inch displays (24MP76HM-S, LG Electronics Inc.). The images of the patient, entry fields of work records, and waveforms and values such as electrocardiogram were presented in the displays. The waveforms and values were changed according to the fluctuation probability set for each patient. In addition, medical equipment such as infusion pumps and drain bags were installed around each bed, depending on the patient setting.

2.2 Experimental Tasks

One participant took the role of leader and the other four participants took the role of performing treatment and care tasks for the patients in their charge. The leader managed tasks in the ward by assisting other members, reassigning persons, and other tasks. The number of patients in the ward varied due to hospitalizations and transfers in the scenario, but the number of patients in charge was always one or two per participant. Changes in staffing according to changes in the number of patients were made at the discretion of the leader. In addition, in some cases, the leader was notified of a request for support from the other ward. In this case, the leader should make a decision on whether or not to provide support and select members from the other four to provide support, depending on the situation in the ward at that point in time.

The treatment and care tasks included in the experiment were designed to simulate actual tasks. The tasks included recording patient information, administering medications, assisting with activities, fluid management, cleanliness care, answering calls from patients, and responding to sudden changes in patients. These tasks included tasks that required more than one person to perform, such as transferring a patient to a stretcher or carrying the stretcher. A schedule describing the tasks that needed to be performed every five minutes was created for each patient, and these tasks were performed according to the schedule. Calls from patients and emergency response were not included in the schedule but were performed in response to changes in the display and audio notifications. Each task was set up in such a way that the situation differed depending on the combination of the probability of a patient's condition changing and the contents of the schedule.

2.3 Measurements

As indices for workload evaluation, heart rate and step count were recorded by a wearable device (Fitbit Versa3, Fitbit, Inc.) attached to the participant's wrist. In addition, the timing of the start and end of the work was recorded by touching the wearable device to a reading device installed in each patient simulator, and the details of the response were recorded by cameras taken in the ward. The log data such as the patient's condition were recorded on the simulator. In

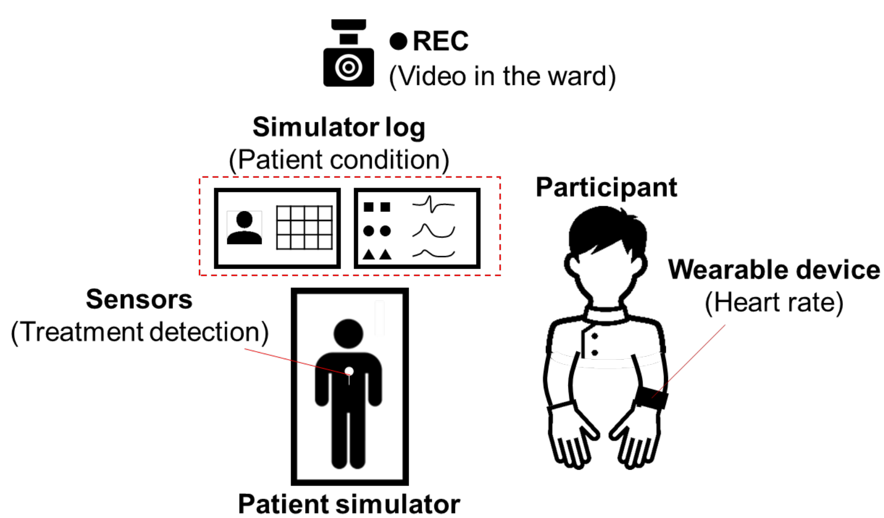

Figure 2. Setting of the devices to measure items in real time during experiment

addition, the patient's sudden change response was recorded by pressure and sound sensors, and this data was reflected in the patient's recovery in sudden changes. Figure 2 shows the items and devices measured in real time during the experiment.

In addition, a subjective evaluation by NASA-TLX (Hart and Staveland, 1988; Miyake and Kumashiro, 1993; Haga and Mizukami, 1996) was obtained to record the participants' workload during the experiment. Six items of NASA-TLX (mental demand, physical demand, temporal demand, performance, effort, and frustration) were answered by scoring a 0 to 100 scale. A notification tone was presented every five minutes during the task, and the experimental participants responded on a tablet terminal as soon as their work at that point was completed. When responding, the participants looked back and evaluated their work from the previous answer time to the current time. After completing the task, a pairwise comparison of the six items was used to select the item that was considered more relevant to the workload.

2.4 Participants

Participants were 65 students belonging to the Department of Nursing participated. The participants were sufficiently trained by viewing the videos to understand the tasks and practicing actually performing the tasks in advance. Although each participant was allowed to participate more than once, the experiment was conducted on a total of 30 pairs, assigned so that the team composition differed from task to task. and the experiment was conducted on 30 teams with different member compositions for each task. This study was conducted after being reviewed and approved by the Research Ethics Review Committee of Keio University Faculty of Science and Technology.

3. Data analysis

3.1 Data acquired in real time in the ward

First, to analyze the relationship between the heart rate acquired by the wearable device and workload, we analyzed the heart rate obtained at 5-second intervals. The heart rate and heart rate variability are indicators that reflect autonomic nervous system activity and have been known to be related to workload (Hancock et al., 1985; Ohsuga et al., 1993; Murata, 1992). The mean heart rate for each analysis interval was calculated and used in the analysis.

Second, to analyze the influence of patient information, we analyzed the simulator log data. As the measurable indicators of patient condition, the cumulative number of sudden changes in patients in the ward was calculated. In addition, the amount number of medical equipment attached to patients in the ward was also calculated.

Third, to analyze the influence of ward conditions such as the amount number of patients, we analyzed the work records and video recordings. Based on the work records and communication during the task, The timing of changes in patient assignments due to hospitalizations, transfers, and leader adjustments were detected. Based on this analysis, the data on the number of patients in charge of each participant were obtained.

3.2 Data of workload during the task

In addition, as an indicator of workload, the weighted workload (WWL) score was calculated based on the scoring of NASA-TLX and comparison data of each item. WWL score is calculated by a weighted sum of the rating scores of the six items. The weight of each item is the number of times the item is selected in a pairwise comparison. This weight is then multiplied by each rating score, summed, and finally divided by the sum of the weighting factors to obtain the weighted workload score.

4. Results and Discussion

The data acquired through the experiment were used to analyze the workload in healthcare during the task. Figure 3 shows the heart rate and WWL score (after linear interpolation) of a participant in a task. The timing of the increase and decrease of heart rate and workload tended to be synchronized with each other, suggesting that they were related to some extent. Thus, the correlation coefficient between heart rate and WWL scores during the two-hour task was calculated for each participant. The mean value of all participants was 0.38, and indicating a weak positive correlation in many cases. The results suggest that the heart rate, which can be easily obtained in real time using a wearable device, is a sufficiently effective indicator for predicting the workload.

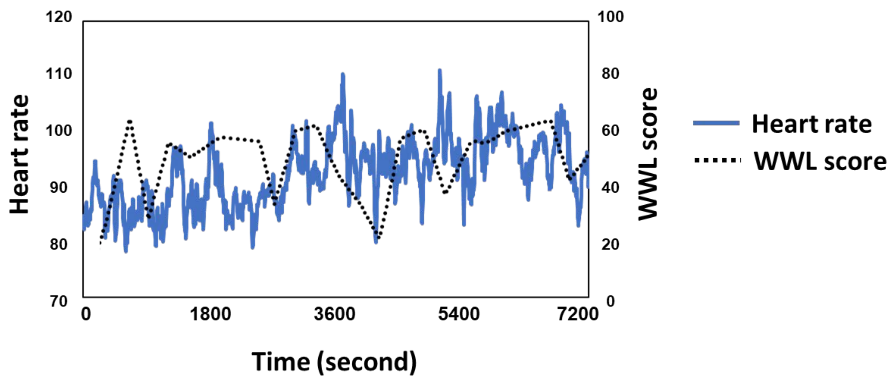

Figure 3. Changes in heart rate and WWL score of a participant during a task

For the patient information, Table 1 shows the cumulative number of sudden changes in the ward and the WWL scores. Although the standard deviation is relatively large, from one-way ANOVA, the main effect of the cumulative number of sudden changes was significant ($F(4, 3387) = 49.4$, $p < 0.01$), and the mean of WWL score tended to be larger the higher the number of sudden changes. In addition, Table 2 shows the amount number of medical equipment such as drain bags and intravenous drips of the patients in charge and the WWL scores. Although the standard deviation is also relatively large, from one-way ANOVA, the main effect of the cumulative number of sudden changes was significant ($F(2, 2701) = 27.1$, $p < 0.01$), and the mean of WWL score tended to be larger the higher the number of medical equipment. In the setting of the experiment, the patient settings were made assuming a specific disease for each patient, and the probability of variation was varied according to the severity of the disease. These results suggested that the measurable indicators affected by the patient settings in the experiment were associated with increasing workload levels. It suggests that measuring situational factors such as the patient's condition is also sufficiently effective for predicting the workload.

Table 1. Relationship between the cumulative number of sudden changes in the ward and the answering WWL score of each participant

Cumulative number of sudden changes	WWL score	
	Mean	Standard deviation
0-5	38.1	21.4
6-10	44.5	22.9
11-15	52.4	24.3
16-20	49.1	21.8
21-	55.3	20.5

Table 2. Relationship between the amount number of medical equipment of the patients in charge and the answering WWL score of each participant

Number of medical equipment of patient in charge	WWL score	
	Mean	Standard deviation
0-5	31.3	21.9
6-10	38.5	22.1
11-	39.9	21.3

For the ward information, Table 3 shows the role of participants in the ward and the WWL scores. Although the standard deviation is relatively large from one-way ANOVA, the main effect of the role of participants was significant ($F(2, 1450) = 15.4$, $p < 0.01$). The mean of the WWL score tended to be higher in the two patients case than in the one patient case, and the mean of the WWL score tended to be even higher in the leader case. The higher workload of the leader may be attributed to the physical workload of assisting other participants as well as the mental workload of managing the ward. The result suggested that the indicator related to the number of treatment and care tasks was associated with increasing workload levels, suggesting that situational factors such as the number of patients also influence workload.

Table 3. Relationship between the cumulative number of sudden changes in the ward and the answering WWL score of each participant

Role of participants	WWL score	
	Mean	Standard deviation
1 patient in charge	34.2	22.3
2 patients in charge	37.7	20.2
Leader	41.7	23.5

The above results suggest that information on participants (healthcare professionals), patients, and wards, which could be obtained in real time using IoT devices during the task, is sufficiently effective for workload prediction, and that these measurable indicators could be expected application to visualize individual workloads in real time by using them in a comprehensive manner.

5. Conclusion

In this study, a simulation experiment was conducted in a simulated hospital ward environment to analyze workloads in healthcare aiming at applying for measuring and visualizing workload in real time. Each of the information on workers, patients, and wards conditions, measured during the experiment showed a certain relationship with the workload variation. It was suggested that the indicators obtained in real time using a wearable device are sufficiently effective for workload prediction, and it is expected that such devices will be used to support by using data related to healthcare professionals.

Acknowledgements

This work was supported by JSPS KAKENHI Grant Number JP12345678.

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