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FATIGUE-RECOVERY SIMULATION MODEL TO ANALYZE THE IMPACT OF NURSING ACTIVITIES ON FATIGUE LEVEL IN AN INTENSIVE CARE UNIT

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ABSTRACT

The main purpose of the current study is to create a simulation model capable of estimating nurses' fatigue levels during a daily shift in an Intensive Care Unit (ICU). The model has been statistically tested and validated by comparing the time study observation data. According to the simulation results, the average fatigue level of ICU nurses was 62.7% ~ 63.6% in a normal workload condition. When the ICU nurses experienced a high workload of regular primary care in the model, the average fatigue level was increased by 5.5% ~ 11.7% compared to the normal condition. For peer support, the fatigue level was increased by 5.7% ~ 7.3%. The main contribution of this work is that the model could provide a new way to estimate the nurses' fatigue levels in different workload conditions and establish specific nurse-patient ratios dynamically to improve patient care in a medical ICU.

1 INTRODUCTION

This study aims to simulate the ICU workflow to predict nurses' fatigue levels. The simulation model was mainly designed to capture the sequence of tasks under similar nursing activity subgroups, the frequency of the nursing tasks, and the duration of each task. To develop a realistic simulation model, the data collected using the Near Field Electromagnetic Ranging (NFER) System and time study manual observation were used. The dataset was collected during two different periods. The first period was from February to March 2020, and the second one was from the beginning of July to the end of July 2020. The category of nursing tasks and their descriptions were based on the research done by Song et al. (2017). In this study, Micro Saint Sharp software was used to develop the ICU nurse workflow simulation model, aiming to forecast nurses' fatigue during a shift. Previous studies have found a strong relationship between high fatigue and performance loss (Rosa 1995; Sagherian et al. 2017; Vargas and Kim 2021). However, not many simulation models have been developed to understand this relationship in the healthcare domain.

To build a simulation model, which is capable of predicting fatigue levels, the direct fatigue was measured as a function of the task duration and its fatigue index. In this study, the fatigue index is based on mental, physical, and effort (focus) demands. In other words, the fatigue index determines how much time a worker is completely exhausted if s/he conducts the task without interruption or break. During the day shift, ICU nurses switch their tasks between periods of fatigue accumulation and a few recovery periods, such as lunchtime and bathroom breaks. Then, the longer task duration will lead to a higher task fatigue index. On the other hand, if a nurse takes a break, the accumulated fatigue is negatively correlated to the task recovery index.

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To validate the simulation model, we compared simulation outcomes with the collected data. The results showed no statistical difference between simulation outcomes and the collected data. The outcomes of the current study show that the developed simulation model could successfully predict the impact of the average fatigue level caused by the workload variation. This model could be used as a powerful tool to identify the key fatigue drivers during a worker's shift.

2 LITERATURE REVIEW

According to Åhsberg (1998), fatigue can take many forms: mental fatigue, lack of alertness, specific muscular fatigue, or general body fatigue. Later, Dode et al. (2016) used the human factors modeling method to analyze muscular fatigue accumulation and recovery, and different aspects of fatigue should be included in human reliability analysis to identify potential risks caused by the fatigue. They aimed to present a systematic attempt to reach a general understanding of perceived fatigue in occupational settings using a questionnaire with 172 verbal expressions describing fatigue. That instrument is called the Swedish Occupational Fatigue Inventory (SOFI). Their study revealed that physical fatigue is correlated to lack of energy, physical exertion, and physical discomfort. Also, mental fatigue is associated with a lack of energy, motivation, and sleepiness.

For the fatigue study in a healthcare domain, Sagherian et al. (2017) investigated whether nurses' acute and chronic fatigue levels were significantly associated with nursing performance. The work-related fatigue was measured by the Occupational Fatigue Exhaustion Recovery (OFER 15) scale, which has 15 items on a 7-point interval scale with responses ranging from strongly disagree (0) to strongly agree (6). Nurses' performance was also measured by an interval scale, using the Nursing Performance Instrument (NPI). This newly developed scale measures nurses' own perceptions of their physical and mental performance while providing patient care. They also investigated the impact of fatigue on work performance and well-being. Their results showed that nurses were mostly female, single, in their twenties, and with a baccalaureate degree. Most nurses worked an 8-hour shift in their work domains, with common overtime.

To calculate the accumulated fatigue, Givi et al. (2015) carried out a factorial experiment, varying the model's independent variables: learning rate, time for total forgetting, fatigue rate, recovery rate, and weights for the learning/forgetting and fatigue/recovery effects, which will depend on the nature of the work routine. In the present work, due to the low repetitiveness/frequency aspect of nursing activities compared to an industrial production system, it is focused only on the fatigue/recovery effects. Givi et al. (2015) assumed three levels of fatigue (or recovery) index, which determines how fast a worker gets exhausted (or recovered) under a work routine (or break): slow, medium, and fast fatigue accumulation index levels. The slow index assumes the worker is completely exhausted after a 12-hour working shift. Medium and fast indexes assume 8-hour and 4-hour working shifts, respectively. The recovery index has the same assumptions; for the slow index, the worker will be completely recovered after a 12-hour break, and so on. In the present study, for each task, the adopted fatigue/recovery index (i.e., slow, medium, or fast) aims to represent the six ratings used by NASA TLX. It is a subjective workload assessment tool that allows users to perform subjective workload assessments on a worker (Hart 2006). NASA TLX consists of mental demand, physical demand, temporal demand, performance, effort, and frustration. Among them, we used three qualitative factors: mental demand, physical demand, and effort.

Regarding fatigue, nurses' acute and chronic fatigue levels were significantly associated with nursing performance. Low recovery between shifts was related to inadequate hours of sleep, waking not fully refreshed, and working overtime. These findings indicate nurses have insufficient time to restore depleted energy levels outside work hours. Those previous studies investigated the relationships between fatigue and performance in hospitals. Also, several studies have been working on real-time fatigue monitoring, such as Ji et al. (2006), who developed a probabilistic framework for monitoring real-time fatigue based on three cognitive behaviors (i.e., eye movement, head movement, and facial expression) and Zhu and Ji (2004) who developed a non-intrusive driver fatigue monitoring system. However, they did not provide forecast or prediction fatigue to understand the impacts on workers' fatigue levels.

3 THE DISCRETE EVENT SIMULATION MODEL

3.1 Data Collection

The Near Field Electromagnetic Ranging (NFER) system was used to record the real-time location of nurses in an ICU (Song et al. 2017). The NFER system architecture includes tracking servers covering the entire ICU area, software, and sensors that recognize nurses' location by tags they carry during their shifts (Dimler et al. 2022). The servers receive and process the data to calculate a tag position. Also, the observers recorded the start time and end time of each task done by the ICU. The observers followed and monitored nurses' activities, recorded the start time and end time of each task, and made notes of any special events during the observation.

3.2 Simulation Model

Discrete event simulation has been a standard technique in analyzing manufacturing systems for more than 50 years(Barnes and Laughery Jr 1997). In this study, Micro Saint Sharp software is used. This discrete simulation software has many applications such as optimization problems, analysis, and results to provide insight or answer specific questions about a system or process. Micro Saint Sharp software is also used in the health care industry (Kim et al. 2019), human factors, and ergonomics (Alexander and Fromm 2019; Bloechle and Schunk 2003).

The simulation model organizes the workflow into seven main activity categories: Handoff, In-room activities, Out-of-room activities, Peer support, Patient clinical processes conversations, Teaching residents/students, and Non-nursing activities.

- ***Handoff*** (in-room or out-of-room) happens when the off-going nurses provide the oncoming nurses with a detailed review of the important issues about the patient's health condition.
- ***In-room activities*** contain all nursing tasks performed inside the patient room and the tasks that support those kinds of activities. They are divided into seven sub-categories: Regular Primary Care, Verification of Supplies of a Room (getting supplies/preparing for a procedure and stocking a room), Comforting/Teaching/Talking with Patients, Electronic Medical Record (EMR) Charting, Cleaning the Patient's Room, Attending Clinical Rounds, and Preparing to/Transporting of Patient. Among them, regular primary care activity is the most important nursing task. It refers to the in-room activities addressing direct patient care except the support tasks. In this simulation model, the regular primary care activity consists of seven sub-categories: Medication (getting, preparing, and administering medication to patients), Performing Procedure, Patient Care, Working on Monitors and Equipment, Closed Curtain (tasks unknown), Lab Specimen Activities (taking lab specimen from a patient and transporting the lab specimen), and Patient's Assessment (initial or focused assessment).
- ***Out-of-room activities*** are related to patient care, but ICU nurses perform those tasks out of the patient rooms. They are composed of EMR charting, performing unit tasks, document revisions, washing hands, staff meetings, electrocardiogram strip review, and taking notes about patients.
- ***Peer support activities*** are conducted in the patient rooms, but the nurse works as a peer supporter this time. Those activities include patient care support, procedure support (physician- or nurse-led), and closed curtain (unknown task).
- ***Patient clinical processes conversations*** are related to patient care, but the patients are not part of those tasks. They consist of talking with other nurses, using ASCOM or table phone, talking with physicians, and talking with patient's family.
- ***Teaching residents/students*** is one part of nurses' duties at the University of Missouri Hospital.
- ***Non-nursing activities*** refer to all activities unrelated to patient care. During those activities, nurses recover from fatigue. They are non-valuable activities (web, phone, etc.), non-valuable

conversation, leaving the unit for restroom/break, lunch break, and waiting for other nurses or healthcare professionals.

3.2.1Simulation Flow Chart

The simulation starts by defining 1) clock time the shift begins, 2) clock time the staff meeting ends, 3) how many tasks should be conducted prior to lunch break, and 4) clock time the next shift nurse is ready to handoff.

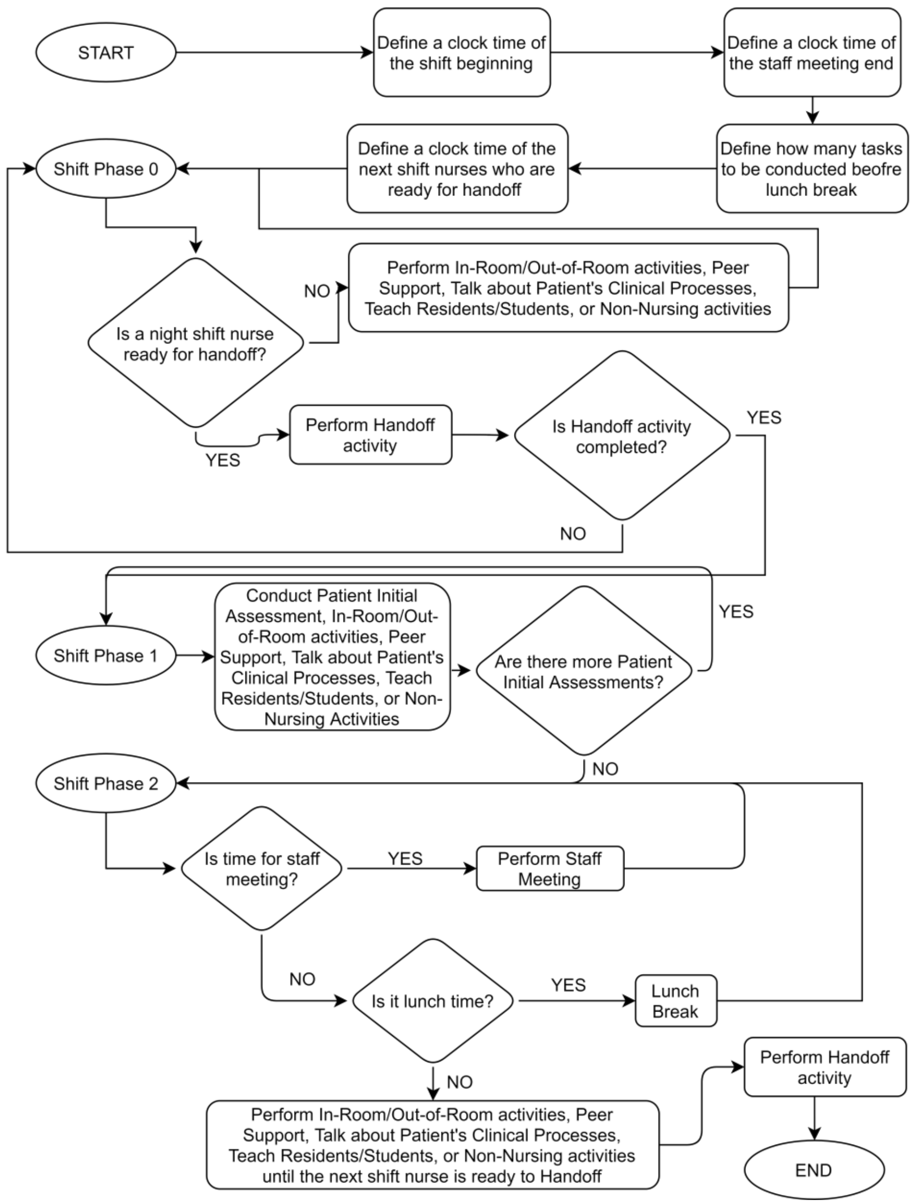

Figure 1: Simulation Flow Chart.

The simulation model was designed to divide the shift into four phases: Phases 0, 1, 2, and 3. **Phase 0** lasts until all handoffs are completed. The model starts the shift and checks the readiness to complete the nurse handoff. If that is true, then move to *Handoff*, and if it is false, do at least one of the other main category tasks. **Phase 0** will continue until all necessary *handoff* tasks are completed. After that, the model moves to **Phase 1**. Both **Phases 1 and 2** refer to the regular shift (i.e., the activities carried out between morning and afternoon *handoff*). The transition from **Phase 1** to **Phase 2** will happen when all necessary patient initial assessments are done. If there is no initial assessment task, then the model jumps straight from **Phase 0** to **Phase 2**. The simulation model chooses which nursing task to perform next based on the probabilities of carrying out that. Those probabilities depend upon the shift phase and the frequency distribution from the observed dataset. Besides, there are two possible special cases in the simulation model: When it is time for a staff meeting and whether the nurse has already done all tasks prior to lunch break. The staff meeting starts at 9:00 am and ends as set at the beginning of the shift, and the simulation models control the moment to go to lunch break similarly.

While the simulation models do not reach the time to go to *handoff*, the simulation models keep running under **Phase 2**. However, when the simulation models reach the time to move to *handoff*, **Phase 3** begins. **Phase 3** will continue until all required handoffs are done, and the shift is over. Finally, the simulation model also calculates the task durations as a function of the observed dataset.

3.2.2Fatigue

Jaber et al. (2013) state that how the human body accumulates fatigue remains an open research question to address in the human physiology literature. However, they treated fatigue accumulation as an exponential function, also adopted in this study (see Equation 1).

$$F_i(t) = F_{i-1} + (1 - F_{i-1})\left(1 - e^{-\lambda_j t}\right),\ 0 < t \leq t_i. \tag{1}$$

Where:
$i = 1, 2, \ldots, n_k$, refers to the i^{th} task conduct during the shift “k”.
$n_k =$ total number of tasks conducted during the shift “k”.
$F_{i-1} =$ residual fatigue, accumulated after the previous task.
$F_0 = 0$.
$t_i =$ time to complete the task “i”.
$j =$ refers to the type of conducted task.
$\lambda_j =$ the fatigue index for task "j".
If $\lambda_j = 0$, then $F_i = F_{i-1}$.

Be x a continuous variable that represents the proportion of a task is completed while the nurse is conducting that task, then

$$x = i - 1 + \frac{t}{t_i},\ 0 < t \leq t_i. \tag{2}$$

$$F_i(x) = F_{i-1} + (1 - F_{i-1})\left(1 - e^{-\lambda_j (x-i+1) t_i}\right), i - 1 < x \leq i.$$

For example, given that $i = 6$, $t_6 = 11.575$ min, $F_5 = 0.46$, $\lambda_j = 0.0192$:

$$F_6(x) = 0.46 + 0.54\left(1 - e^{-0.0192(x-5)11.575}\right), 5 < x \leq 6\ .$$

According to Givi et al. (2015), both the fatigue accumulation index and the recovery speed index were determined. They use three fatigue and recovery indexes for the low, medium, and fast levels. The low fatigue index means that if a worker conducts a task, without interruption, after 12 hours, s/he will be completely exhausted. For the medium level, 8 hours to exhaustion, and the high level, 4 hours for exhaustion.

In this study, for each task, the adopted fatigue/recovery indexes aim to represent the six ratings from NASA TLX: mental demand, physical demand, temporal demand, performance, effort, and frustration. The present assessment tool was used to define whether an activity demand is neutral to or invigorating in terms of mental demand, physical demand, and effort. The analysis consists of classifying the three features as +1 if the characteristic increases fatigue, 0 if the characteristic is not significant to fatigue, and -1 if the characteristic decreases fatigue, or is invigorating. Then, if a task presents the three features increasing fatigue, it has a high-level fatigue index. If only two features increase fatigue, it has a medium-level fatigue level. And if only one feature increases fatigue, it has a low-level fatigue index. The same criteria are used to define the recovery indexes. This process is done after interviewing a healthcare expert. Finally, the fatigue range is from 0, at the beginning of the shift, to 1 (100%), and the fatigue equation returns the nurse accumulated fatigue level after conducting an activity.

3.2.3Recovery

Konz (2000) suggests that the human body recovery function is exponential, with maximum benefit in the earlier phases of the recovery period. This is consistent with the recovery equations used by Jaber et al. (2013) and adopted in this study (see Equation 3).

$$F_i(t) = F_{i-1}e^{-\mu_j t},\ 0 \le t \le t_{i.} \tag{3}$$

Where μ_j = the recovery index for task "j".
Using the transformation presented in Equation 2:

$$F_i(x) = F_{i-1}e^{-\mu_j(x-i+1)t_i},\ i-1 < x \le i.$$

For example, given that $i = 57$, $t_{57} = 32.531$ min, $F_{56} = 09$, $\mu_{N6} = 0.0192$:

$$F_{57}(x) = 0.9e^{-0.0192(x-56)32.531},\ 56 < x \le 57.$$

The Recovery equation returns the nurse accumulated fatigue level after conducting a non-nursing activity.

3.3 Average Fatigue Level

Equation 4 is the general equation for calculating the average fatigue level during the shift. Whether a task increases, does not affect, or decreases fatigue, its contribution to the shift average fatigue level is calculated using Equations 5, 6, or 7, respectively.

$$F_{avg} = \frac{1}{n_k}\sum_{i=1}^{n_k}\int_{i-1}^{i} F_i(x)dx \tag{4}$$

$$\int_{i-1}^{i} F_i(x)dx = \int_{i-1}^{i}\left[F_{i-1} + (1-F_{i-1})\left(1-e^{-\lambda_j(x-i+1)t_i}\right)\right]dx,$$

$$\int_{i-1}^{i} F_i(x)dx = \int_{i-1}^{i}\left[1-(1-F_{i-1})e^{-\lambda_j(x-i+1)t_i}\right]dx,$$

$$\int_{i-1}^{i} F_i(x)dx = 1 - \frac{(1-F_{i-1})\left(1-e^{-\lambda_j t_i}\right)}{\lambda_j t_i} \tag{5}$$

$$\int_{i-1}^{i} F_i(x)dx = F_{i-1},\ \text{given } \lambda_j = 0 \tag{6}$$

$$\int_{i-1}^{i} F_i(x)dx = \int_{i-1}^{i} F_{i-1}e^{-\mu_j(x-i+1)t_i}dx,$$

$$\int_{i-1}^{i} F_i(x)dx = \frac{F_{i-1}}{\mu_j t_i}\left(1-e^{-\mu_j t_i}\right). \tag{7}$$

Where:
F_{avg} = the average fatigue level during the shift.
n_k = the total number of tasks conducted during the shift "k".
$i = 1, 2, \ldots, n_k$, refers to the i^{th} task conduct during the shift "k".
t_i = time to complete the task "i" time to complete the task "i".

F_{i-1} = residual fatigue, accumulated after the previous task.
$F_0 = 0$.
j = one of the 46 different possible tasks in the simulation model.
λ_j = the fatigue index for task "j".
μ_j = the recovery index for task "j".

4 RESULTS

4.1 Task Frequencies

The simulation model turned out the frequency for 40 different tasks, from a total of 46, simulated with 200 replicates. It is important to mention that only the nursing tasks carried out during the regular shift were compared. It means that verbal report, verbal report along with initial patient assessment, and waiting to give or receive a report to nurse were not compared. Also, a staff meeting (morning huddle) and lunch break activities were not compared because they do not happen as a function of frequency distributions, but they depend on the nurse's availability. We considered them binary events.

This section compares the observed data to the simulation outcomes. For a statistical level of 0.05, all simulated tasks present no significant statistical difference between the simulation results and observed data of both periods (February to March 2020 and July 2020). Hence, the simulation model successfully represents the nurses' workflow in terms of task frequency. To illustrate the comparison of the observed and simulated data, Figure 2 shows the out-of-room EMR charting frequency distribution for February to

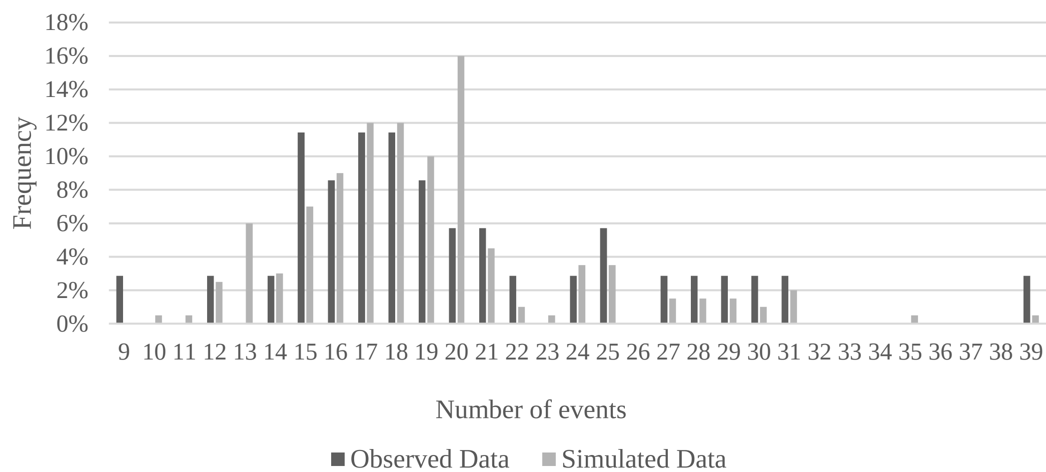

Figure 2: Distribution for out-of-room EMR charting.

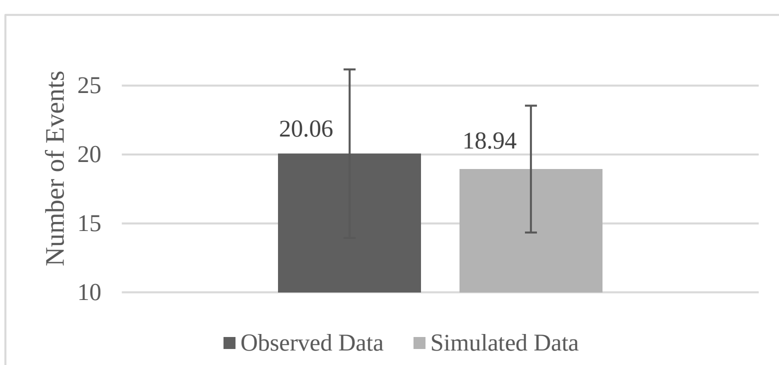

Figure 3: Average number of out-of-room EMR charting. P-value of 0.309.

March 2020, the most frequent task during a shift. Figure 3 compares the average number of out-of-room EMR charting.

4.2 Task Duration

This section compares the observed data to the simulation outcomes (200 runs). Table 1 shows the statistical results of all nursing task categories. The results present no statistical difference between the simulation results and the observed data for both February to March 2020 and July 2020 data.

Table 1: Comparison between observed and simulated data in terms of task category proportions.

Category	Sample Type	Mean	SD	Statistic	p
Handoff	Observed	5.3%	2.3%	-0.355	0.723
	Simulated	5.4%	2.0%		
In-room Activities	Observed	33.9%	9.6%	-0.332	0.742
	Simulated	34.4%	7.1%		
Out-of-room Activities	Observed	15.7%	5.7%	0.752	0.456
	Simulated	15.0%	4.3%		
Peer Support	Observed	6.4%	4.2%	0.187	0.852
	Simulated	6.2%	3.4%		
Patient Clinical Processes Conversations	Observed	17.8%	7.4%	0.099	0.922
	Simulated	17.7%	4.3%		
Teaching Residents/Students	Observed	1.7%	3.7%	-1.098	0.273
	Simulated	2.3%	2.9%		
Non-nursing Activities	Observed	19.2%	6.3%	0.284	0.776
	Simulated	18.9%	5.8%		

4.3 Sensitivity Analysis

For the sensitivity analysis, experiments were run varying the number of patient procedures, ***regular primary care activities,*** and ***peer support activities*** in steps about 1 standard deviation, from -3 to +3, to assess their impact on the average nurse fatigue level (see Table 2). In this study, those types of tasks are considered important fatigue drivers because of their frequency, duration, and intensity (fatigue index). Table 2 also shows that an (a) increase (decrease) in ***regular primary care*** or ***peer support activities*** implies less (more) the other task type.

Table 2: Impact on the average fatigue level due to changes in regular primary care and peer support.

Scenario	Average Fatigue Level	Average Fatigue Level
	Feb, Mar-20	**July 20**
Normal shift	**Mean: 63.6% SD: 7.0%**	**Mean: 62.7% SD: 6.9%**
-70% ~ -78% of *regular primary care*	Mean: 58.2% SD: 7.0%	Mean: 56.9% SD: 7.1%
-47% ~ -53% of *regular primary care*	Mean: 59.8% SD: 7.0%	Mean: 59.1% SD: 7.1%
-23% ~ -28% of *regular primary care*	Mean: 61.9% SD: 6.8%	Mean: 61.2% SD: 7.0%
+23% ~ +26% of *regular primary care*	Mean: 65.3% SD: 6.7%	Mean: 67.4% SD: 6.3%
+47% ~ +53% of *regular primary care*	Mean: 66.9% SD: 6.3%	Mean: 71.4% SD: 5.8%
+67% of *regular primary care*	Mean: 68.2% SD: 6.2%	Mean: 75.3% SD: 5.2%
-100% of *peer support*	Mean: 61.0%	Mean: 60.5%

	SD: 6.9%	SD: 6.8%
-81% ~ -89% of *peer support*	Mean: 61.6% SD: 6.9%	Mean: 60.7% SD: 6.7%
-37% ~ -42% of *peer support*	Mean: 62.2% SD: 7.0%	Mean: 62.1% SD: 6.9%
+40% ~ +43% of *peer support*	Mean: 64.7% SD: 6.6%	Mean: 65.9% SD: 6.6%
+82% ~ +94% of *peer support*	Mean: 67.8% SD: 6.4%	Mean: 68.4% SD: 6.5%
+117% ~ +133% of *peer support*	Mean: 69.3% SD: 6.0%	Mean: 70.0% SD: 6.0%

4.3.1 Comparing the Scenarios

To analyze the impact of the simulated average fatigue level in different scenarios, Welch's test was used. Welch's test showed at least one difference between paired scenarios of key independent variables. After that, post hoc tests were performed to identify the nature of the differences. These post hoc tests aim to identify significant differences between pairs of scenarios while maintaining acceptable levels of Type I error. This study also used the Games-Howell method for the post hoc comparisons. Figure 4 shows a summary of the results of those comparisons.

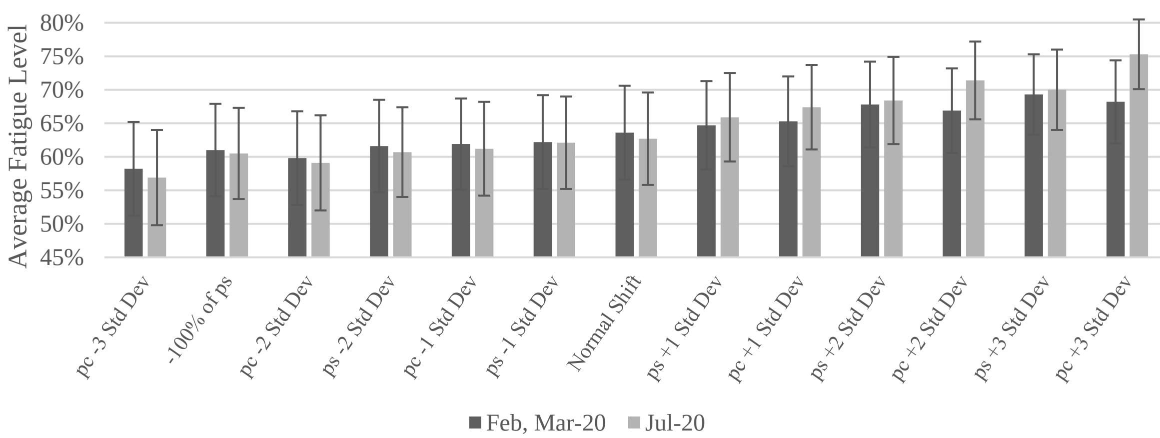

Figure 4: Post hoc tests summary.

5 DISCUSSIONS AND CONCLUSION

According to the results, the average fatigue level of ICU nurses was 62.7% ~ 63.6% in a normal workload condition. When the ICU nurses experienced a high workload of regular primary care in the model, the average fatigue level was increased by 5.5% ~ 11.7% compared to the normal condition. For peer support, the fatigue level was increased by 5.7% ~ 7.3%.

For the nursing task frequencies are the task durations, a typical day shift lasts an average of 12 hours, so the task frequencies should fit in the total shift duration. Also, they must present an equivalent duration distribution to the observed data. According to Table 1, as an example of the comparison between the observed and simulation task durations, all task categories presented a p-value greater than the significance level of 0.05. The same test was conducted for the February to March 2020 dataset, and all results verify that the simulation results are not different from the observed data. Besides the task frequencies and durations, the simulation model followed similar sequence patterns in the time study dataset. For instance, given that the ICU nurse has finished performing a procedure, the nurse proceeds to the next task according to the observed sequence possibility in the time study dataset.

From the sensitivity analysis results, the average number of ***Primary Patient Care Activities*** is about 2.2 times higher than the number of ***Peer Support Activities***. Also, a variation of the former task group impacts more the time available to conduct other nursing tasks. Because of that, any variation of the number of ***Primary Patient Care Activities*** can magnify much more nurses' average fatigue levels than variations of ***Peer Support Activities*** (see Table 2).

Regarding the Feb, Mar-20 model, the scenario ***+40% ~ +43% of peer support*** does not significantly differ from the **normal shift**. The further increments in ***Peer Support Activities*** are significant in the Feb, Mar-20 model. On the other hand, decrements in ***Peer Support Activities*** are significantly different from the **normal shift.** Although ***-37% ~ -42% of peer support*** is similar to ***-81% ~ -89% of peer support*** , which is similar to ***-100% of peer support***, ***-37% ~ -42% of peer support*** is significantly different from ***-100% of peer support***. Besides, all variations (both positive and negative) in ***Regular Primary Care Activities*** are substantially different from the normal shift and different from each other.

Regarding the Jul-20 model, ***-37% ~ -42% of peer support*** does not imply a significant difference from the **normal shift.** The further decrements in ***Peer Support Activities*** are significant in the Jul-20 model, despite **-**81% ~ **-**89% of peer support is not significantly different from ***-100% of peer support***. On the other hand, increments on ***Peer Support Activities*** are substantially different from the **normal shift**. All variations (both positive and negative) in ***Regular Primary Care Activities*** are significantly different from **the normal shift** and different from each other.

Comparing the models, from the ***Peer Support Activities*** perspective, the results are all similar for the same type of variation. For instance, the scenario ***+40% ~ +43% of peer support*** for Feb, Mar-20 is similar to the Jul-20 model. Similarly, ***+82% ~ +94% of peer support*** for Feb, Mar-20 is similar to the Jul-20 model, and so on. From the ***Regular Primary Care Activities*** perspective, except for the scenario ***-23% ~ -28% of regular primary care***, negative variations imply higher fatigue levels for the Feb, Mar-20 model, while positive variations imply higher fatigue levels for the Jul-20 model.

Those outcomes show that the developed simulation model could successfully predict the impact of the average fatigue level caused by the workload variation. Although the model requires further analysis to make a strong relationship between predicted fatigue levels and the workload variation, the main contribution of this work is a robust simulation model, which is statistically proven by comparing the observed dataset and the ICU nurse workflow main characteristics. This model could be used as a powerful tool to identify the key fatigue drivers during a worker's shift. In other words, this simulation model could apply to fatigue prediction, estimating workload in conducting a particular task, and optimizing a system or specific activity, such as EMR charting. Besides a medical ICU environment, this simulation architecture could apply to other healthcare units. For example, an emergency room might be the one potential unit where we might get substantial benefits from using this simulation model. Finally, this simulation model will be able to apply to other production systems, which have various tasks in a non-standardized order.

One limitation in this model is the fatigue and recovery indexes. This study assumes three levels for the indexes, low, medium, and high, depending on the nature of the activity. Hence, it would be better to collect the data to apply more accurate fatigue and recovery indexes in the simulation model, which is a more acceptable outcome for an ICU environment.

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