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

A Thesis

presented to

the Faculty of the Graduate School

at the University of Missouri-Columbia

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

By

Vitor de Oliveira Vargas

Dr. Jung Hyup Kim, Thesis Supervisor

The undersigned, appointed by the Associate Vice Chancellor of the Office of Research and Graduate Studies,

have examined the thesis entitled

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

Presented by

Vitor de Oliveira Vargas,

A candidate for the degree of

Master of Science,

and hereby certify that, in their opinion, it is worthy of acceptance.

Dr. Jung Hyup Kim

Dr. James S. Noble

Dr. Kangwon Seo

Dr. Laurel Despins

ACKNOWLEDGMENTS

To God all honor and glory for this achievement in my life!

I also thank my wife, Jamille, for her unconditional support on this journey. There is no way of not sharing this achievement with the person who was by my side in all moments, mainly when the pressure and stress seemed to be unbearable.

To my children, Lucas and Giovana, thank you for being my sources of lightness, purity, and joy.

I also dedicate this victory to my parents, Reinaldo and Ana. They have always been cheering me on from afar and unfortunately God took him before he could witness my achievement.

Finally, I thank my advisor, Dr. Kim, for the safe guidelines, always pushing me to go further.

Contents

List of Illustrations

List of Tables

ABSTRACT

Although nursing is physically and mentally strenuous, not many studies have been done yet to find the impact of the key groups of tasks on nurses' average fatigue level and workflow. So, this study aims to understand the relationships among the key activities that impact the nurses' average fatigue level in an Intensive Care Unit (ICU).

Nurses' time-study and real-time location data have been used to develop a simulation model in two different periods: February to March 2020 and July 2020. Two Hierarchical Task Analysis charts were generated from the collected data, one for each period, and used as the foundation for the fatigue-recovery simulation model. Both simulation models have been statistically tested and validated by comparing the time study observation data.

Different scenarios of all nursing activities' frequencies (number of conducted tasks during a shift) and task sequences (number of times tasks are conducted continuously prior to a break) were simulated as independent variables. The dependent variable is their impacts on the nurses' predicted average fatigue levels during a shift.

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 to establish specific nurse-patient ratios dynamically to improve patient care in a medical ICU. In this study, it was found that the major drivers for nurses' fatigue in an ICU shift is the number of times nurses conduct tasks in sequence without a break (number of task sequences), followed by the number of patient care or procedures, and peer support activities conducted in shift. However, the limitations in this study are the lack of the ratio number of nurses/number of patients during the shifts, the number of patients assigned to the assessed nurses, and

regarding to the fatigue and recovery indexes. In this study, it is assumed three levels for the indexes, low, medium, and high, depending on the nature of the activity. It is recommended that, for the sake of more accurate results, in future studies, fatigue is monitored by a real-time method, in that way, there will be an estimated fatigue and/or recovery index for every single nurse task.

CHAPTER 1: INTRODUCTION

According to Düzkaya and Kuğuoğlu (2015), nurses are the members of the medical team who are with the patients for a longer time. Within typical health organizations, nurses are the largest workforce and play a vital role in the quality of care and health promotion, making up most of the hospital staff (Moghadam *et al.*, 2020). Generally, the nursing workload is determined by the time spent on patient care, nursing activities, and the skills needed to care for the patient. This study is focused on the ICU nurses' workflow, which is analyzed based on three main characteristics: Sequence of tasks under the same subgroup, frequency of the tasks, and tasks' durations. According to Moghadam *et al.* (2020), the ICU is an environment that provides care for patients with severe clinical conditions. ICU nurses are exposed to extremely high physically and mentally demanding workloads.

Nursing is physically and mentally strenuous, and performance loss and fatigue are expected during the shift (Sagherian *et al.*, 2017). Fatigue and performance decrements are safety hazards for both patients and nurses in an intensive care unit (ICU); that is why this research is interested in the average fatigue reached by a nurse during a working shift.

This study is based on the ICU nurses' workflow using the Near Field Electromagnetic Ranging (NFER) System and time study manual observation data collected during two different periods. The first period refers to February and March 2020, and the second one refers to July 2020. The tasks observed during the data collection were based on the task descriptions in Song and Kim's research (2017). NFER System is an indoor global positioning system (GPS) and Kolodziej and Hjelm (2006) present several applications to local positioning systems, particularly in healthcare. They are used to find assets, caregivers, and patients, implying less time needed to look for people and medical equipment, reducing inventory and labor, and increasing patient satisfaction. Another healthcare application is for emergency calls, for fast and automatic locating of the caller.

So, the motivation for this work is the lack of studies about the impact of the key groups of tasks and sequence of tasks on nurses' average fatigue level during a shift, the dependent variables, and this study aims to analyze that impact by simulated experiments varying the frequencies and sequences of nursing tasks randomly, the independent variables, in a screening experiment. Then, the objective here is to find the frequency and sequence task configurations that turn out high levels of risk both for patients and nurses. In this study, the instantaneous fatigue level is measured as a function of the task duration and its fatigue index, which in its turn, depends upon how mental, physical, and effort demanding the task is. Actually, the fatigue index determines how much time a worker is completely exhausted if s/he conducts the task without interruption. During the working shift, nurses switch between periods of fatigue accumulation and few recovery periods, such as lunch time. So, the average fatigue level is measured by $F_{avg} = \frac{1}{n_k}\sum_{i=1}^{n_k}\int_{i-1}^{i} F_i(x)dx,\ i = 1, 2, \ldots, n_k$, where n_k is the total number of tasks in a simulated shift "k". Moreover, the longer the task duration and the greater the task fatigue index, the greater is $F_i(x)$. On the other hand, during a break, $F_i(x)$ is negatively correlated to the task recovery index.

Two HTA (Hierarchical Task Analysis) charts were developed to develop simulation models using the Micro Saint Sharp software. With the models on hand, the second part of the study is to compare the main simulation outcomes with the collected data. To compare the ICU nurse shifts during the period that goes from February to March 2020 and the period of July 2020, this study will use a hypothesis test, checking whether there is statistical evidence that task frequency and duration averages from observed and simulated data are equivalent, using RStudio software.

Third, the next step is to run screening experiments followed by a sensitivity analysis, simulating 1,000 runs for each scenario, varying the independent variables' levels, using an experiment with random factors, and the JMP software as the application tool.

Finally, this study aims to understand the contribution of each key factor to fatigue level. Then, task sequences before and after lunch, performing procedures, patient care, and peer support are the most important drivers of fatigue during a nurse shift in an Intensive Care Unit (ICU) for both periods.

CHAPTER 2: LITERATURE REVIEW

2.1 Occupational Fatigue Screening

Lu *et al.* (2017) detailed the several existing fatigue scales, questionnaires, and surveys in the literature, the assessed type of fatigue and target population as well. Regarding the working population, they listed the Swedish Occupational Fatigue Inventory (SOFI) of Åhsberg (1998), the Occupational Fatigue Exhaustion Recovery (OFER) of Winwood *et al.* (2005), and the Chalder Fatigue Scale (CFQ 11) of Jackson (2015). On the other hand, Lu *et al.* (2017) aim to screen manufacturing workers for the severity of fatigue. They designed a survey to investigate: Demographics (age, gender, height, and weight), fatigue-related characteristics (amount of sleep, smoking habits, alcohol intake, exercise frequency, and experience/length of stay in the same position), work-related exposures (repetitive tasks and duration of work), self-perceived fatigue, perceived fatigue level, frequency and interference, body parts affected, and individual fatigue coping mechanisms. They found that the top three perceived fatigue causes were lack of sleep, work stress, and shift schedule. Their method could be applied to the ICU environment, but this study is more interested in how a work shift affects nurses than how nurses perceive their fatigue causes.

According to Åhsberg (1998), fatigue can take many forms: mental fatigue, lack of alertness, specific muscular fatigue, or general body fatigue. Dode *et al.* (2016) added that human factors modeling is concerned with muscular fatigue accumulation and recovery. Different aspects of fatigue can be included in human reliability analysis to identify potential risks, such as mental demand, physical demand, period performing a task, performance, and effort. That study 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). That experiment reduced the expressions to 25 divided into five factors: Lack of energy, physical exertion, physical discomfort, lack of motivation, and sleepiness. Finally, that study found a correlation between those five factors and the nature of the work. In summary, fatigue due to physical work is correlated to lack of energy, physical exertion, and physical discomfort; fatigue due to mental work is correlated to lack of energy, lack of motivation, and sleepiness; and fatigue from night work is correlated to sleepiness. In comparison to the present work, Åhsberg (1998) did a qualitative analysis of fatigue. This study needs a methodology for measuring fatigue to understand the impact of the key groups of tasks and sequence of tasks on nurses' average fatigue level during a shift.

Winwood *et al.* (2005) stated that the most serious issues of occupational fatigue are when it becomes chronic. So, in their study, they developed the Occupational Fatigue Exhaustion Recovery (OFER) scale to measure work-related fatigue. OFER scale assesses physical and emotional health, including energy level, sleep health, emotional health, social isolation, and functional health. It also estimates work-demand features, such as work pace, mental and emotional demand, physical effort, peer support, and supervisor support. Although it is quite comprehensive, it is hard to adapt it to the real-time fatigue prediction demand of the present work.

The CFQ 11 scale of Jackson (2015) is a self-administered questionnaire for measuring the extent and severity of fatigue within both clinical and non-clinical, epidemiological populations. It may be used in studies about occupational research and allows for straightforward comparisons between studies and populations.

Sagherian *et al.* (2017) investigated whether nurses' acute and chronic fatigue levels were significantly associated with nursing performance, specifically the performance of physical and mental nursing care activities. 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), a developed scale that 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 in the close past. Their results showed that nurses were mostly female, single, in the twenties, and with a baccalaureate degree. In the work domain, most nurses worked on an 8-hour shift, with common overtime. 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. Despite that study presents some similarities with the present study, as both investigate the same relation work/fatigue, the outcomes do not provide any forecast of fatigue during a work shift. That study did not identify the main fatigue drivers during a shift. That is why the assessment of the impacts on nurses' fatigue level and workflow makes this work innovative.

Lim and Son (2022) assessed two questionnaire-based methods of measuring fatigue: The Korean version of the Multidimensional Fatigue Inventory (MFI-K) and the modified Chalder Fatigue Scale (mKCFQ), which was motivated by the absence of biological parameters for fatigue and appropriate instruments for assessing people's fatigue level. Lim and Son's (2022) methodology was based on a statistical experiment, a survey with 70 respondents, divided into three groups of fatigue levels, according to their responses. They found that both methods were significantly correlated and equally useful. Although their results prove that both MFI-K and mKCFQ are effective in measuring fatigue, none of those are suitable to be applied in this work because they do not offer a tool or method to predict the real-time nurse fatigue level.

According to Min *et al.* (2021), occupational fatigue is prevalent among nurses and adversely affects nurse and patient outcomes. They measured occupational fatigue and recovery using the Korean version of the Occupational Fatigue Exhaustion/Recovery Scale, consisting of 15 items with three subscales: Acute fatigue, chronic fatigue, and intershift. They found that overtime hours and number of night shifts were significant influential factors of acute and chronic fatigue, and recommended policies limiting the number of working hours per week. Once more, they do not offer a tool or method to predict the real-time nurse fatigue level, which is not useful in this work.

2.2 Measuring Nursing Workload

According to Miranda *et al.* (2003), the nursing activities score (NAS) can be used to measure nursing workload at an individual patient level, regardless of the severity of illness, case mix, and type of ICU. Their study aimed to determine the nursing activities that best describe workload in the ICU and attribute weights to these activities. The score describes the average time consumption instead of the severity of illness. Miranda *et al.* (2003) suggest that the NAS measures the consumption of nursing time in the ICU. Although the greater the NAS, the greater will be how faster a nurse gets fatigued during an activity, that is, the fatigue index, it is not possible to derive a direct correlation of fatigue index and NAS, at least without an experiment.

According to Padilha *et al.* (2008), it is important to identify nurses' requirements in an ICU environment not only for purposes of patients' quality care, but also for their safety. Their study investigated the association between NAS and some patient variables, such as gender, age, length of stay, ICU discharge, treatment, illness severity, and Therapeutic Intervention Scoring System-28 (TISS- 28). They used multiple logistic linear regression analyses to determine which variables would work as predictors of higher ICU nursing workload. The study concluded that length of stay, illness severity, and TISS-28 are all associated with higher NAS. Moreover, the most important finding is that higher NAS was associated with increased mortality. So, the takeaway is that nurses' fatigue in an ICU must be managed for the sake of the care quality and safety of patients and nurses as well. However, like in the study of Miranda *et al.* (2003), it is still not possible to derive a direct correlation of fatigue index and NAS without an experiment.

2.3 Measuring Fatigue Analytically

Givi *et al.* (2015) correlates human error and the interactions learning-forgetting and fatigue-recovery analytically. Their model is able to dynamically measure the human error rate and reliability with time. They used the mathematical model developed by Jaber *et al.* (2013) called the learning–forgetting–fatigue–recovery model, which provides analytical measures to capture the effects of the human learning–forgetting and fatigue–

recovery on the productivity and process time. In the present study, concerns about nurses' and patients' safety are much more important than productivity, that is, the goal is to perform nursing tasks well rather than fast, in order to heal patients. The learning-forgetting-fatigue-recovery model answers why a worker cannot carry out a work routine with a steady performance. Learning because if someone performs a task several times, every time s/he repeats it, s/he will do it faster. However, under fatigue, the worker is supposed to make more mistakes, and the completion time tends to increase. On the other hand, forgetting is because, after a break, the worker loses part of his/her expertise, and the task completion time is supposed to increase. And finally, after a break, due to recovery, s/he is supposed to make fewer mistakes, so the completion time tends to decrease. However, the present study does not aim to find or predict any worker error rate, but as mentioned before, to assess the impacts on nurses' fatigue level and workflow, since fatigue is a safety hazard that has implications for both nurses and patients (Sagherian *et al.*, 2017). Vargas and Kim (2021) have applied the same mathematical model to simulate fatigue in a maintenance routine.

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) assume 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 that 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, that is, 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, being it slow, medium, or fast, aims to represent the six ratings used by NASA TLX, mental demand, physical demand, temporal demand, performance, effort, and frustration, in three qualitative factors, representing the original NASA TLX's ratings: Mental demand, physical demand, and effort. According to NASA's website, NASA-TLX is a subjective workload assessment tool that allows users to perform subjective workload assessments on a worker.

2.4 Real-time Fatigue Monitoring

Some studies for real-time fatigue monitoring, such as Ji et al. (2006), have developed a probabilistic framework for monitoring real-time fatigue based on three cognitive behaviors: Eye movement, head movement, and facial expression. Also, Zhu and Ji (2004) developed a non-intrusive driver fatigue monitoring system, using cameras to acquire driver images.

Ji *et al.* (2006) developed a probabilistic framework based on the Bayesian networks for modeling and real-time inferring human fatigue by integrating information from various sensory data and certain relevant contextual information. The contextual information refers to binary conditions, and the correspondent probabilities, such as sleep environment (random noise, light, heat, and humidity), sleep state (anxiety), work environment (temperature, weather, and noise), sleep quality (sleep environment, sleep time, napping, and sleep state), physical conditions (sleep disorders), circadian (time-zone and time), and work conditions (workload and work type). Under those contextual conditions, fatigue is predicted/measured by some indicators, such as facial expression (yawn frequency and facial muscle), eye movement (eyelid movement and gaze), and head movement. The framework of Ji *et al.* (2006) allows to conduct fatigue inference over time and under uncertainty, but still needs some improvements. The challenge here is to find and adapt the most adequate method for an ICU environment. A real-time fatigue monitoring system would allow a much more accurate prediction of the fatigue/recovery indexes.

CHAPTER 3: METHODOLOGY

3.1 Data Collection

The data used in this study was collected using the same architecture (see Figure 3.1) as Song and Kim (2017) did. The Near Field Electromagnetic Ranging (NFER) system was used to record the real-time location of nurses in an ICU, while the observers recorded the start time and end time of each task done by the ICU.

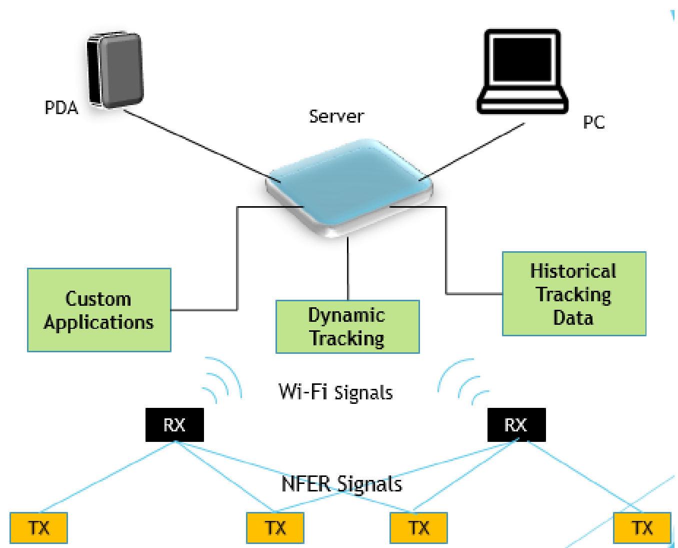


Figure 3.1. The architecture of the NFER system.

According to Schantz (2007), NFER technology is emerging as a preferred real-time locating system (RTLS) solution for operation in complicated indoor propagation environments, such as ICU. Schantz *et al.* (2011) present results that NFER systems yield an accurate location to within 1 m about 83% of the time, with potential for 30 cm, which is completely acceptable for this study.

The NFER system architecture consists of tracking servers covering the whole ICU area, a tracking software installed in an appropriate laptop, and sensors that recognize nurses' location by tags they carry during their shifts. The servers receive and process the data to calculate a position of a tag.

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. The observers organized the activities using the same codes used by Song and Kim (2017), as shown in Appendix A.

3.2 HTA Charts

According to Stanton (2006), there are three principles governing the theory of Hierarchical Task Analysis (HTA). The first principle states that HTA is meant to describe a system in terms of its goals. The second principle is that HTA allows a system to be broken down into sub-operations in a hierarchical manner. The final principle refers to an existing relationship among goals and sub-goals, and the rules to achieve sub-goals and the final objective. Based on that description, the development of the HTA will allow building the simulation models as closer as possible to reality.

The data set of the two periods were organized in two different HTA charts, Appendixes B and C represent the charts for Feb, Mar-20 and Jul-20 periods, respectively. The HTA charts aim to represent the nurses' workflow as a function of two main characteristics. The first one is the task frequencies, which are the number of times a task is repeated during a shift. The HTA charts order the tasks as a function of the greatest frequencies within each group of activities. The second feature refers to the task sequences, and the HTA charts reproduce those by the accomplishment plans for each group or subgroups of tasks.

The HTA charts organize both period workflows in the same 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. However, as mentioned above, the activities within the main tasks are placed in a different order in each period as a function of their frequencies, from the highest to the lowest one. For example, in the HTA chart of Feb, Mar-20, the task Patient Care is labeled as 2.1.3, while in the HTA chart of Jul-20, it is labeled as 2.1.4. Appendix D presents the procedure (Plan 0) to carry out the nurse workflow, which is the same for both periods.

3.2.1 Handoff

Handoff happens when the off-going nurse provides the oncoming nurse with a detailed review of the important issues about the patient's health condition. It may be conducted outside of the patient room (V2) or inside the patient room (V2+PC1), when the verbal report is conduct along with patient initial assessment. Figure 3.2 shows the procedure to carry out handoffs (Plan 1), which is the same for both periods.

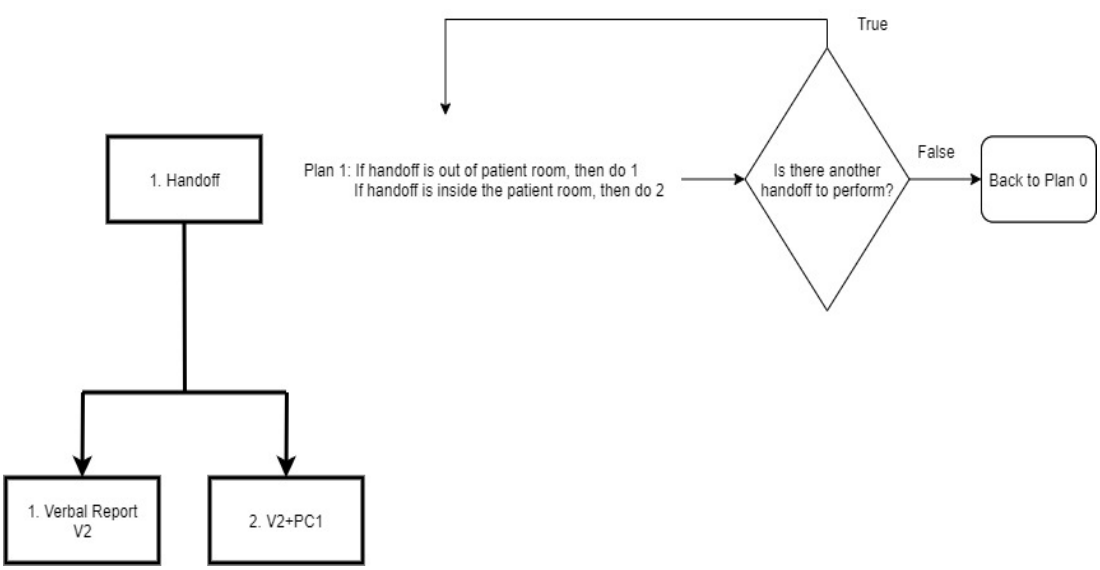


Figure 3.2. Do Handoff for both periods.

3.2.2 In-room Activities

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. Figures 3.3 and 3.4 show the plans to carry out the in-room activities in Feb, Mar-20 and Jul-20, respectively. After careful observation, it is noted that the tasks are presented in different orders, reflecting that the task frequencies are different in the periods of analysis.

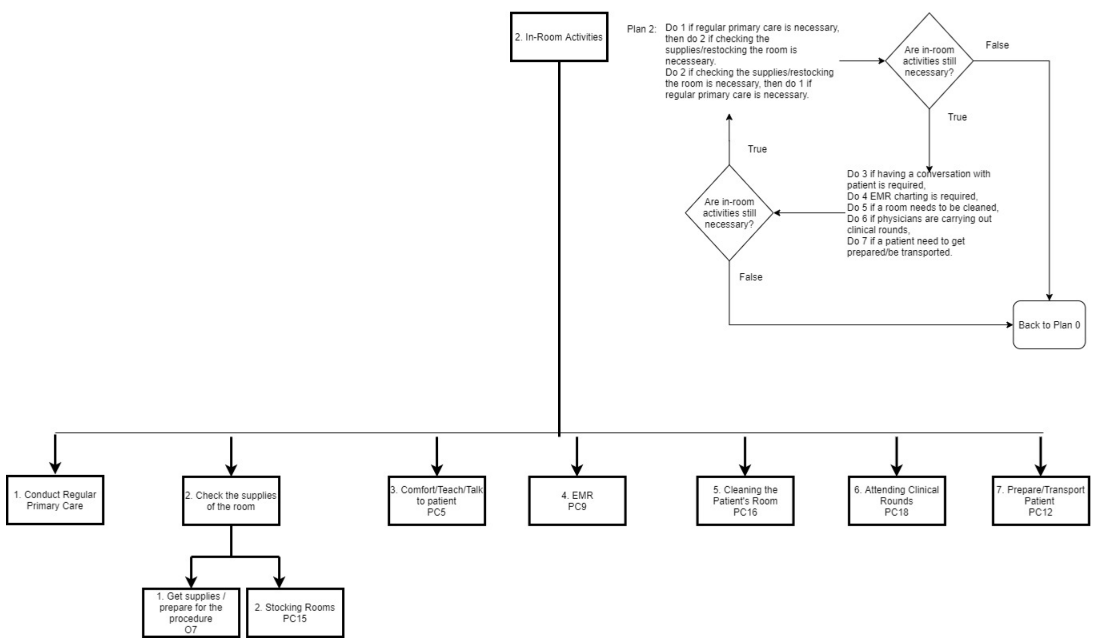


Figure 3.3. Do in-room activities (Feb, Mar-20).

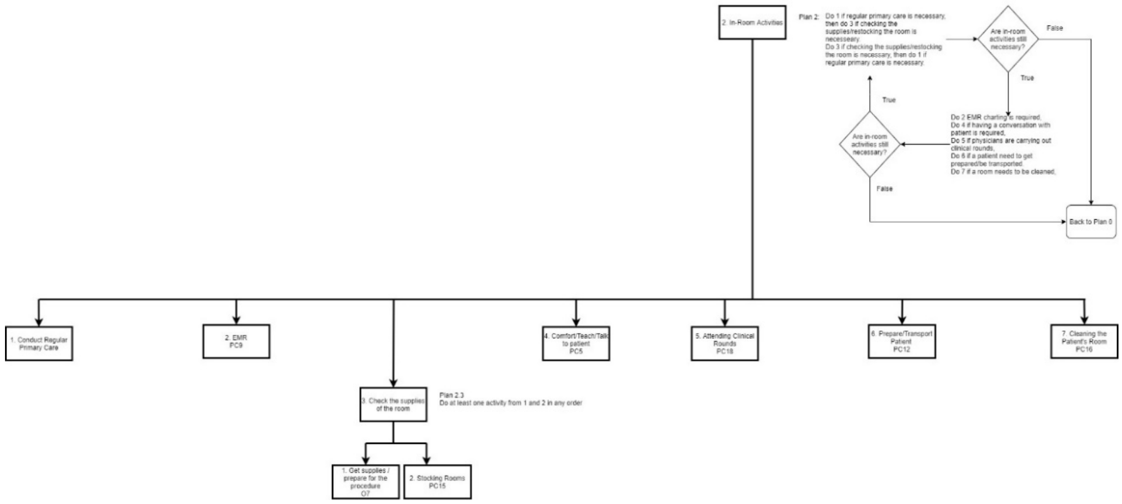


Figure 3.4. Do in-room activities (Jul-20).

3.2.2.1 Regular Primary Care Activities

The regular primary care is the most important nursing task category. It refers to the in-room activities except the support tasks. In this simulation model, the regular primary care category 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). Figures 3.5 and 3.6 show the plans to carry out the regular primary care activities in Feb, Mar-20 and Jul-20, respectively. After careful observation, it is noted that the tasks are presented in different orders, reflecting that the task frequencies are different in the periods of analysis.

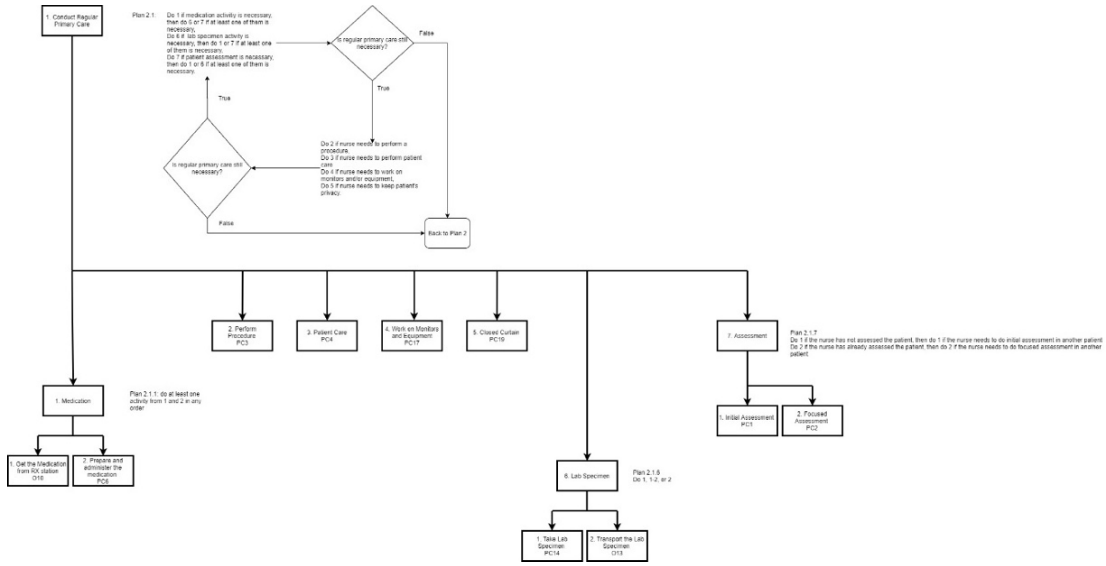


Figure 3.5.Do regular primary care (Feb, Mar-20).

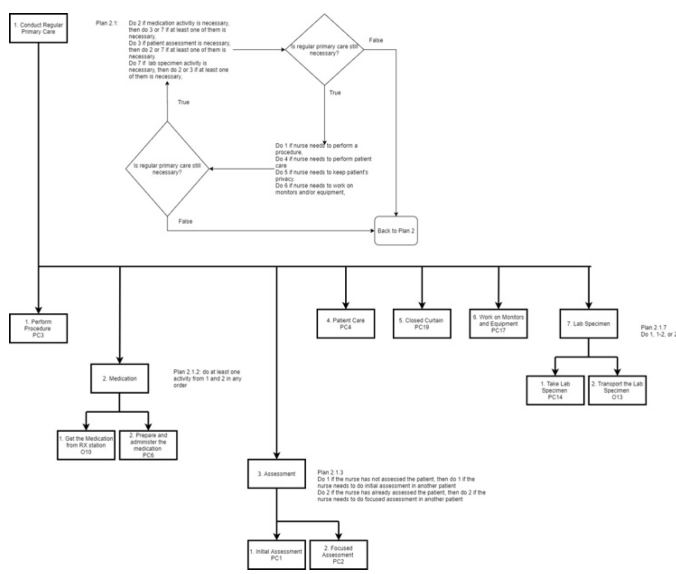


Figure 3.6. Do regular primary care (Jul-20).

3.2.2.1.1 Lab Specimen Activities

Lab specimen activities are composed of taking lab specimens from a patient and transporting the lab specimen. Figures 3.5 and 3.6 show the plans to carry out the regular primary care activities, including the lab specimen kinds in Feb, Mar-20 (Plan 2.1.6) and Jul-20 (Plan 2.1.7), respectively.

3.2.2.1.2 Medication Activities

Medication activities involve getting, preparing, and administering medication to patients. Figures 3.5 and 3.6 show the plans to carry out the regular primary care activities, including the medication kinds in Feb, Mar-20 (Plan 2.1.1) and Jul-20 (Plan 2.1.2), respectively.

3.2.2.1.3 Patient's Assessment

Patient's assessment is composed of initial and focused assessments. Figures 3.5 and 3.6 show the plans to carry out the regular primary care activities, including the patient's assessment in Feb, Mar-20 (Plan 2.1.7) and Jul-20 (Plan 2.1.3), respectively.

3.2.2.2 Verification of Supplies of a Room

Verification of supplies of a room is composed of getting supplies/preparing for a procedure and stocking a room. Figures 3.4 and 3.5 show the plans to carry out the in-room activities, including the verification of supplies of a room in Feb, Mar-20 (Plan 2.2) and Jul-20 (Plan 2.3), respectively.

3.2.3 Out-of-room Activities

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 strips revision, and taking notes about patients. Figures 3.7 and 3.8 show the plans to carry out the out-of-room activities in Feb, Mar-20 and Jul-20, respectively. After careful observation, it is noted that the tasks are presented in different orders, reflecting that the task frequencies are different in the periods of analysis.

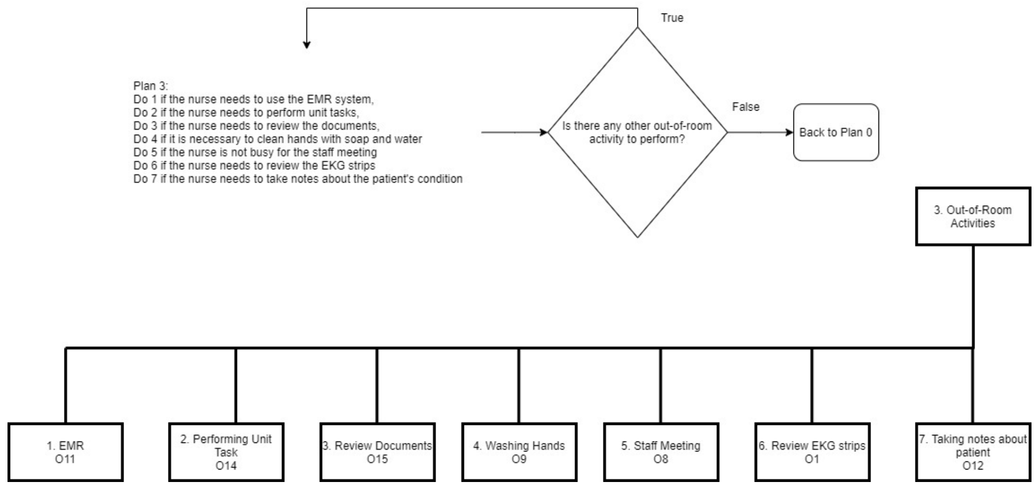


Figure 3.7. Do out-of-room activities (Feb, Mar-20).

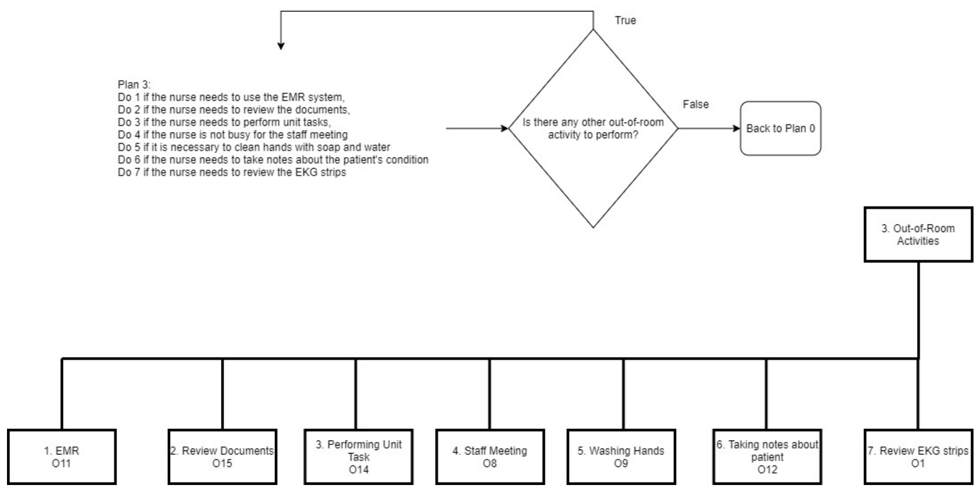


Figure 3.8. Do out-of-room activities (Jul-20).

3.2.4 Peer Support

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). Figures 3.9 and 3.10 show the plans to carry out peer support in Feb, Mar-20 and Jul-20, respectively. After careful observation, it is noted that the tasks are presented in different orders, reflecting that the task frequencies are different in the periods of analysis.

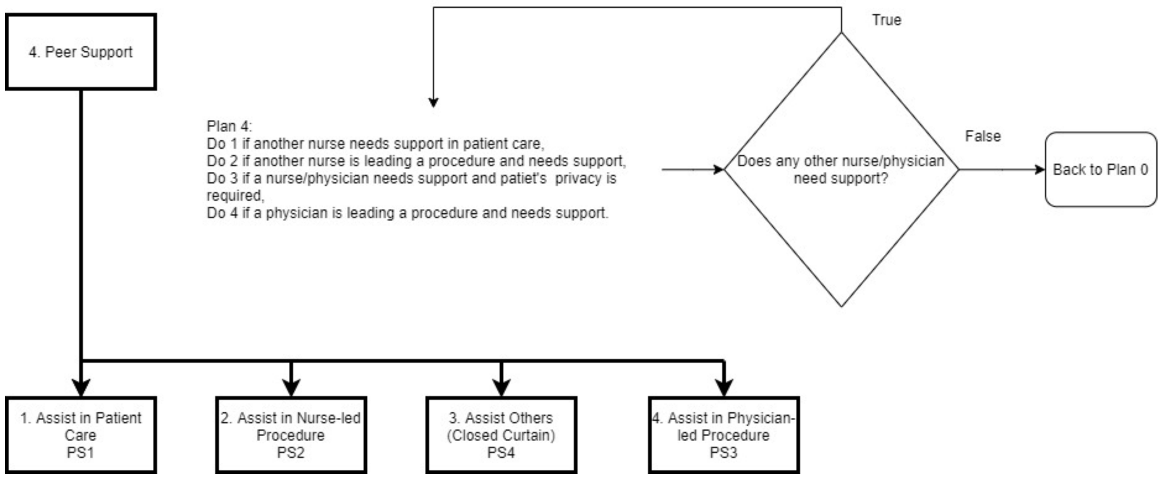


Figure 3.9. Do peer support (Feb, Mar-20).

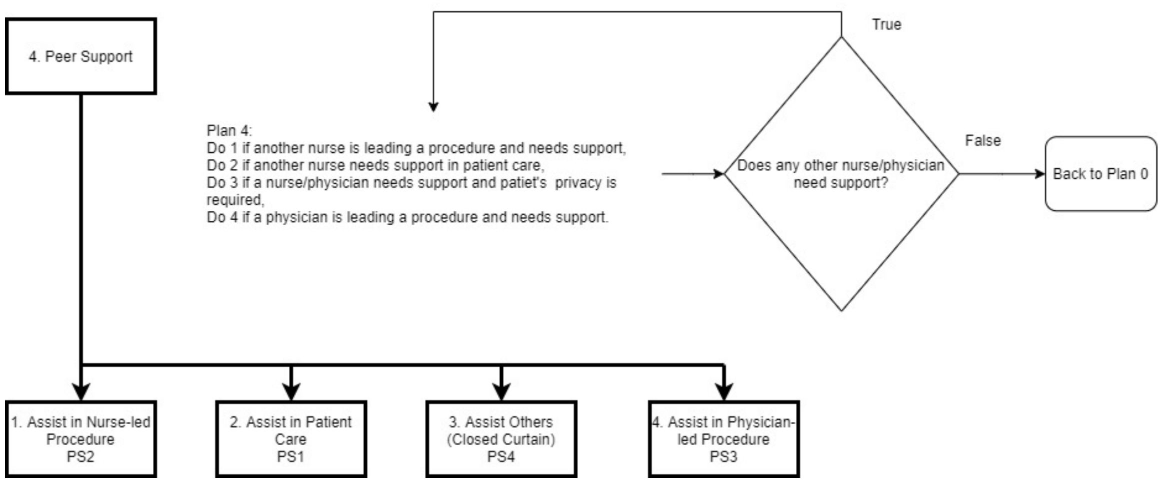


Figure 3.10. Do peer support (Jul-20).

3.2.5 Patient Clinical Processess' Conversations

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. Figures 3.11 and 3.12 show the plans to carry out patient clinical processes conversations in Feb, Mar-20 and Jul-20, respectively. After careful observation, it is noted that the tasks are presented in different orders, reflecting that the task frequencies are different in the periods of analysis.

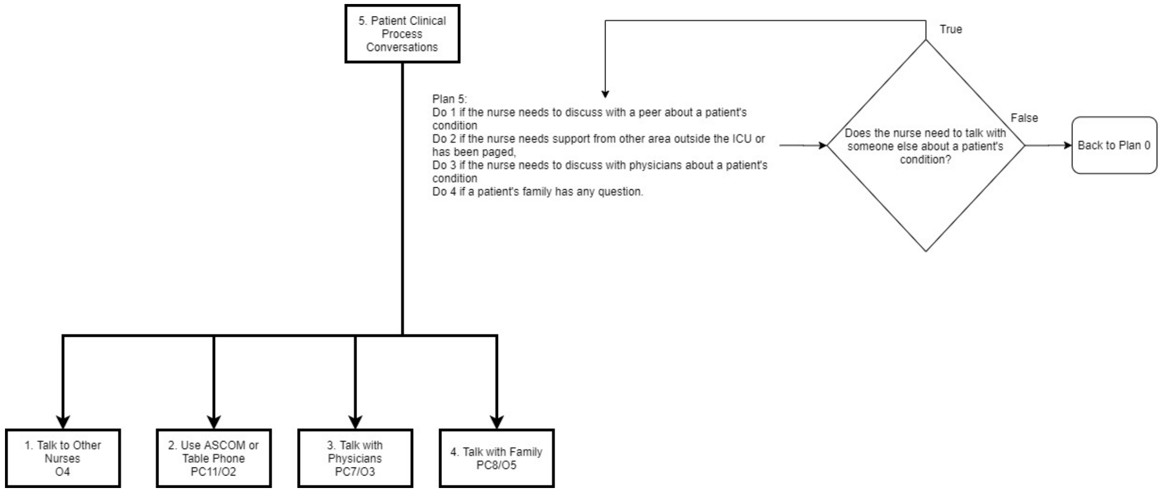


Figure 3.11. Do patient clinical process conversations (Feb, Mar-20).

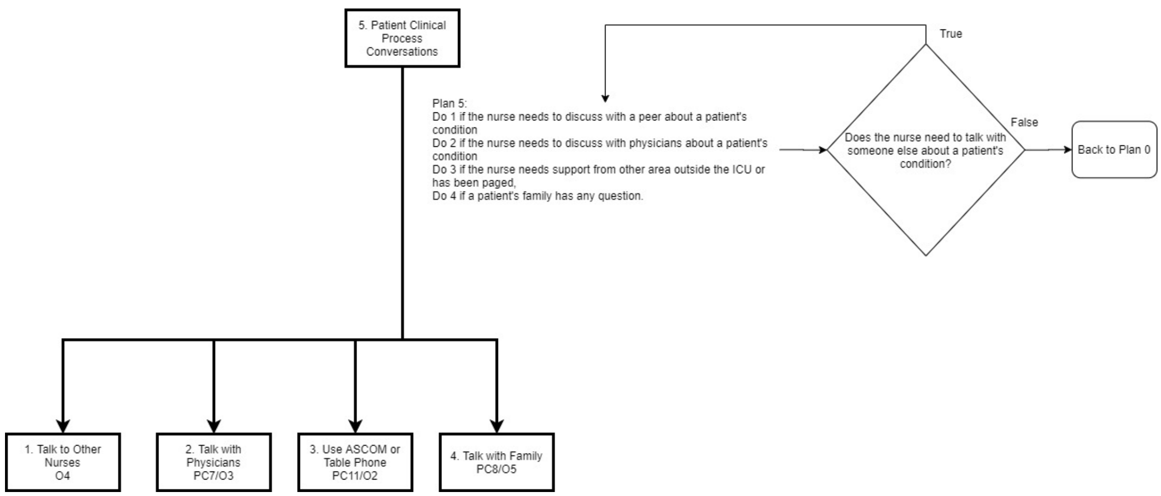


Figure 3.12. Do patient clinical process conversations (Jul-20).

3.2.6 Teaching Residents/Students

Teaching residents/students is one part of nurses' duties at the University of Missouri Hospital. Although it is a single task, not a group of tasks, it also belongs to the HTA chart main categories, so its performing procedure is under Plan 0 (Appendix C).

3.2.7 Non-nursing Activities

Finally, 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. Figure 3.13 shows the plans to carry out non-nursing activities and represents those tasks for both periods, Feb, Mar-20 and Jul-20.

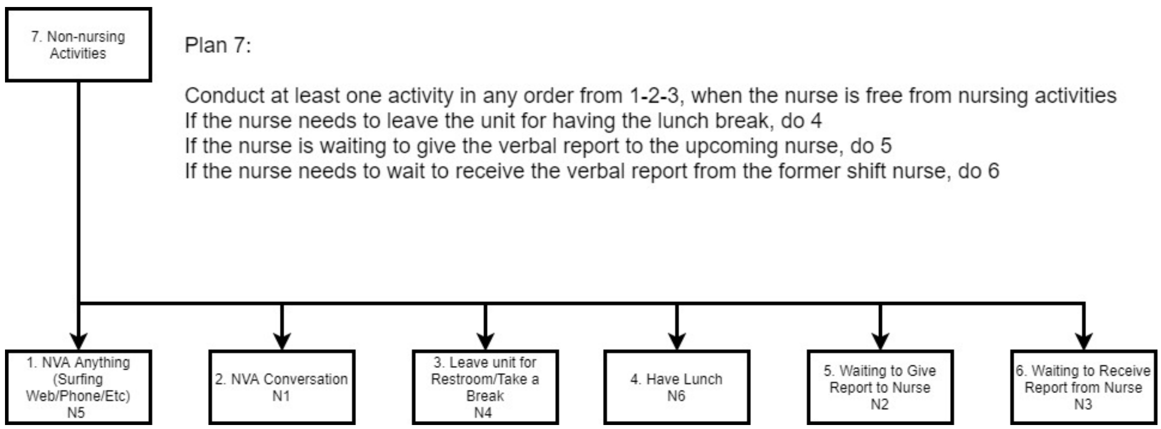


Figure 3.13. Do non-nursing activities.

3.3 Simulation Model

Discrete event simulation has been a standard technique in the analysis of manufacturing systems for more than 50 years (Barnes and Laughery Jr., 1997). The Micro Saint Sharp software has many applications such as optimization problems, analysis, and results to provide insight to or answer specific questions about a system or process. In the manufacturing industry, variables such as throughput rate and cycle time may be monitored, as well, looking for optimal schedules and new facility layouts. Also, Micro Saint Sharp software is applied to the health care industry, human factors, and ergonomics, which are the focus of this work.

The developed HTA charts (Section 3.2) are the foundation for developing two simulation models, one for each period. The only difference between the HTA charts and the simulation models is that the latter has an additional task: Unknown Activities. The reason for adding this task in the simulation models is that during the data collection, the observers used to have breaks, check the system accuracy, have lunch, or do any other tasks that preclude them from collecting data. During those breaks, nurses were performing one of the described tasks in the HTA chart, but it ended up recorded as unknown. The observed unknown tasks were 4.96 minutes and 19.26 minutes from February to March 2020 and July 2020, respectively.

The simulations start with the initialization codes that call for four functions: Shift_Beginning (section 3.3.5.1), Staff_Meeting_End (section 0), Tasks_to_Lunch (section 3.3.5.3), and Time_to_Handoff (section 3.3.5.4). Those are basic functions for running the simulations.

3.3.1 Plan 0

As mentioned before, the HTA charts are the foundation to build the simulation models. The models start with Plan 0 (Appendix D), which was designed to dismember the shift in 4 phases: phases 0, 1, 2, and 3. Phase 0 lasts until all handoffs are completed. From Plan 0, the model starts the shift and asks, “Is the former shift nurse available for handoff?”. If it is true, go to Plan 1 (Handoff), and if it is false, do at least one of the Plans from 1 to 7. Phase 0 will continue until the answer to the next question (“Did nurse complete all necessary handoffs?”) is true, then the model goes to phase 1. Both phases 1 and 2 refer to the regular shift, that is, the activities carried out between morning and afternoon handoffs. The transition from phase 1 to phase 2 will happen when all necessary patient initial assessment (PC1) is done. If there is no PC1 task to be done, the model jumps straight from phase 0 to phase 2. The PC1 activities are carried out under Plans 2.1.7 (Figure 3.5) and 2.1.3 (Figure 3.6) for February to March 2020 and July 2020, respectively.

Under Plan 0, the simulation models choose which plan to perform next based on the probabilities to carry out a plan. This logic does not work only for Plan 0, but for all plans within the HTA charts. Those probabilities come from the scheduled number of tasks previously defined by the function Events (see Section 3.3.5.5). The number of tasks scheduling is stored in variables according to Equations (3.1 to (3.6. Then, under Plan 0, the probability for the models going to Plan 3 is a_3/N, or under the Plan 2.1, the probability for the models performing the task 2.1.4 is $a_{2\_1\_4}/a_{2\_1}$. It is worthwhile mentioning that those probabilities are dynamic, that is, if $a_{2\_1\_4} = 2$, $a_{2\_1} = 45$, $a_2 = 62$, and $N = 154$ initially, after conducting the task 2.1.4, then $a_{2\_1\_4} = 1$, $a_{2\_1} = 44$, $a_2 = 61$, and $N = 153$, until all tasks are completed ($N = 0$).

$$a_{2\_1\_k} = \sum_{l=1}^{2} a_{2\_1\_k\_l}\,, \begin{cases} k = 1, 6, 7, \text{for Feb, Mar-20 model} \\ k = 2, 3, 7, \text{for Jul-20 model} \end{cases} \tag{3.1}$$

$$a_{2\_1} = \sum_{k=1}^{7} a_{2\_1\_k} \tag{3.2}$$

$$a_{2\_j} = \sum_{k=1}^{2} a_{2\_j\_k}\,, \begin{cases} j = 2, \text{for Feb, Mar-20 model} \\ j = 3, \text{for Jul-20 model} \end{cases} \tag{3.3}$$

$$a_{5\_j} = \sum_{k=1}^{2} a_{5\_j\_k}\,, j = 2, 3, 4^{1} \tag{3.4}$$

$$a_i = \sum_{j=1}^{n} a_{i\_j}\,, \begin{cases} if\ i = 1\ or\ 6, n = 2 \\ if\ i = 2\ or\ 3, n = 7 \\ if\ i = 4\ or\ 5, n = 4 \\ if\ i = 7, n = 6 \end{cases}{}^{2} \tag{3.5}$$

$$N = \sum_{i=1}^{7} a_i + u \tag{3.6}$$

Where,

[1] Tasks 5.2, 5.3, and 5.4 can be carried out inside or outside the patient room. For out-of-room tasks k=1, and for in-room tasks k=2. For example, $a_{5\_4\_1}$ means the scheduled number of tasks for out-of-room 5.4 activity, that is O5 in both HTA charts.

[2] Task 6 can be carried out inside or outside the patient room. For out-of-room k=1, and for in-room k=2. For example, a_{6_2} means the scheduled number of tasks for in-room 6 activity, that is PC10 in both HTA charts.

$a_{i\_j\_k\_l}$ =number of scheduled tasks for the activity i.j.k.l
N =total number of scheduled tasks
u =number of scheduled unknown tasks

Besides, other than the probabilities to carry out Plans 1, 2, until 7, there are two possible special cases in the Plan 0: When it is time for a staff meeting (do Plan 3) and whether the nurse has already done all tasks prior to a lunch break (do Plan 7). The staff meeting starts at 9:00 am and ends according to the function Staff_Meeting_End (see Section 0), and the simulation models control the moment to go to lunch break by the function Tasks_to_Lunch (see Section 3.3.5.3).

While the simulation models do not reach the time to go to handoff (see Section 3.3.5.4), calculated by the sum of the time the shift begins (see Section 3.3.5.1) and the simulation ongoing duration, the simulation models keep running under phase 2, that is, the answer to the question in Plan 0 "Is next shift nurse available for handoff?" is false. However, when the simulation models reach the time to go to handoff, the answer to that question is true, and phase 3 begins. Phase 3 will continue until all required handoffs are done, that is, the answer to the second question, "Did the nurse complete all necessary handoffs?" is true, and the shift is over. Also, in some simulation runs, the scheduled total number of tasks is done, and the simulation has not already reached the time to go to handoff. When this happens, the simulation models call for the function Add_Events (see Section 3.3.5.6) and may do it repeatedly until the time to go to handoff is reached, and the simulation models go to phase 3.

Moreover, in the level 1 routines (Plans 1, 2, …, 7) and lower levels of the HTA charts, after the nurse has finished one task/sub-routine, the next task/sub-routine to be carried out will follow conditional probabilities based on the time-study data set. Figure

3.14 presents one of the many possible sequences in the simulation models. From the Figure, as the sequence gets longer, the number of the possible paths decreases, and the conditional probabilities get larger. It is important to mention that the simulation models also treat the cases where there are no more scheduled tasks to be conducted. So, in these cases, the conditional probability becomes 0. In other words, if under Plan 2.1, the model went to task 2.1.2 and there is no more PC4 task to be conducted, the probability of going to task 2.1.3 is going to 0 instead of 0.016.

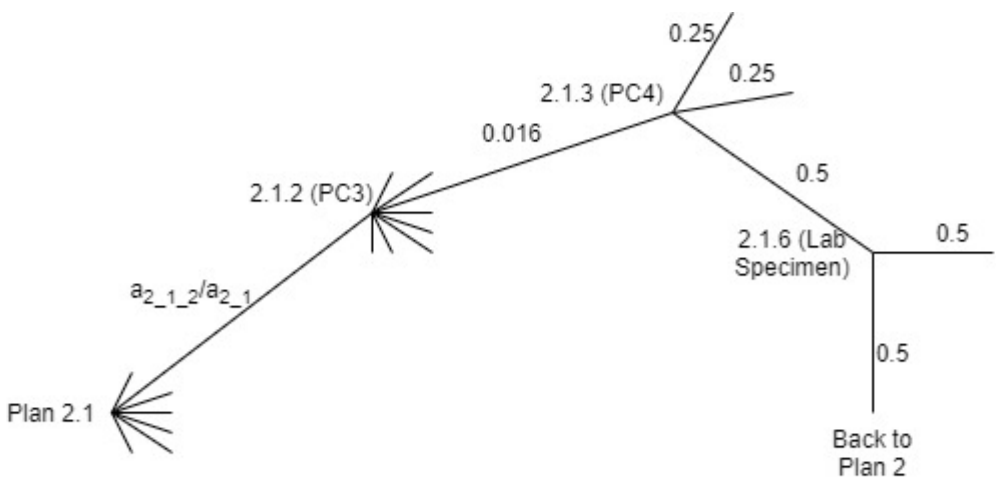


Figure 3.14. Conditional probabilities to conduct the sequence 2.1.2-2.1.3-2.1.6 (Feb, Mar-20 simulation model).

Furthermore, the simulation models use the equation (3.7 to control the task sequence under a plan. For instance, using the sequence 2.1.2-2.1.3-2.1.6 (Figure 3.14) once more, $id_{2.1_0} = 0$, $id_{2.1_1} = 10x0 + 2 = 2$, $id_{2.1_2} = 10x2 + 3 = 23$, and $id_{2.1_3} = 10x23 + 6 = 236$.

$$id_{i_n} = 10id_{i_{n-1}} + j \quad (3.7)$$

Where,

id_{i_n} = the variable that tracks the task sequence under Plan "i".

$id_{i_0} = 0$.

i = the plan index.

n = the counter of the number of tasks under Plan "i".

j = the j^{th} task to be conducted under Plan "i".

Also, besides task frequencies and sequences, the simulation models calculate the task durations by the function Task_Duration (see Section 3.3.5.7). Moreover, every time the simulation models perform a valuable activity (Plans 1 to 6), they call for the Fatigue function (see Section 3.3.5.8). Every time they complete a non-valuable activity (Plan 7), they call for the Recovery function (see Section 3.3.5.9).

3.3.2 Plans 1, 3, 4, and 5

Plans 1 (Figure 3.2), 3 (Figures 3.7 and 3.8), 4 (Figures 3.9 and 3.10), and 5 (Figures 3.11 and3.12) are quite similar to each other, which is to exhaust all the possible tasks sequences under those plans. For instance, the questions "Is there another handoff to perform?" (Plan 1), "Is there any other out-of-room activity to perform?" (Plan 3), "Does any other nurse/physician need support?" (Plan 4), and "Does the nurse need to talk with someone else about a patient's condition?" (Plan 5) are for the simulation models return to the beginning of the plan and cover any possible sequence. It is important to highlight that, since the HTA charts were designed to exhaust all the sequences under a plan, it is impossible to repeat the same plan in sequence; that is, the sequence 5-5 is not possible. What is allowed is to conduct the same single task twice in a sequence, but not the same plan/routine.

3.3.3 Plans 2 and 2.1

Plans 2 (Figures 3.3 and3.4) and 2.1 (Figures 3.5 and 3.6) are similar to each other, not only to exhaust all the possible task sequences under those plans, but also to separate the sub-routines from the single tasks under them. They recalled that the HTA charts were designed to exhaust all the sequences under a plan and not allow the repetition of the same plan in sequence. For example, under Feb, Mar-20 model, Plan 2 (Figure 3.3), it is possible conducting the sub-routines 2.1 or 2.2 alone, as well the sub-routine sequences 2.1-2.2 and 2.2-2.1, but there is no way to repeat them unless any tasks from 2.3 to 2.7 are conducted before. On the other hand, tasks from 2.3 to 2.7 may be conducted in sequence while the simulation stays in Plan 2 and the conditional probabilities allow them to do so (see Section 3.3.1).

3.3.4 All Other Plans

Plans 2.1.1, 2.1.6, 2.1.7 (Figure 3.5), 2.2 (Figure 3.3) from Feb, Mar-20 model, 2.1.2, 2.1.3, 2.1.7 (Figure 3.6), 2.3 (Figure 3.4) from Jul-20 model, are also similar in the extent they have got only two tasks subordinate to them. All possible task combinations are described in the HTA charts.

Finally, Plan 7 (Figure 3.13) is unique within the HTA charts. This plan has six tasks subordinate to it, although only tasks 7.1, 7.2, and 7.3 may configure a task sequence; the other require special conditions to be conducted. Task 7.4 (Have Lunch) is defined under Plan 0 (Section 3.3.1). Task 7.5 is possible only during shift phase 3, and Task 7.6 only during shift phase 0.

3.3.5 Functions

3.3.5.1 Shift_Beginning

The nurse shift does not begin at the same time every day, so this function returns the exact time a nurse starts her shift. Table 3.1 shows the cumulative frequency of the time nurses used to start the shift based on the time-study data. The simulations generate a random number between 0 and 1, 0.34, for example. Based on Table 3.1, the shifts would start at a random time from 7:11 to 7:12 am and from 7:10 to 7:11 am in the Feb, Mar-20 and Jul-20 simulation models, respectively. This function is necessary because some tasks depend on clock time, for example, the staff meeting is scheduled to start at 9:00 am.

Table 3.1. Cumulative frequency for the time nurses start their shifts.

Minutes after 7:00 am	Feb, Mar-20	Jul-20
6 – 7	-	2.7%
7 – 8	5.6%	8.1%
8 – 9	16.7%	13.5%
9 – 10	22.2%	32.4%
10 - 11	30.6%	59.5%
11 - 12	50.0%	62.2%
12 - 13	58.3%	64.9%
13 - 14	63.9%	75.7%
14 - 15	75.0%	97.3%
15 - 16	94.4%	98.0%
16 - 17	95.8%	98.7%
17 - 18	97.2%	99.3%
18 - 19	100.0%	100.0%

3.3.5.2 Staff_Meeting_End

The staff meeting does not end at the same time every day, so the simulations use the cumulative frequency distribution for returning the time the staff meeting used to end (see Table 3.2). The simulations generate a random number between 0 and 1, 0.03, for example. Based on Table 3.2, the staff meeting would finish at a random time from 9:02 to 9:03 am and from 9:05 to 9:06 am in the Feb, Mar-20 and Jul-20 simulation models, respectively.

Table 3.2. Cumulative frequency for the time staff meeting ends.

Minutes after 9:00 am	Feb, Mar-20	Jul-20
2 - 3	3.7%	-
3 - 4	7.4%	-
4 - 5	11.1%	-
5 - 6	14.8%	12.0%
6 - 7	22.2%	24.0%
7 - 8	29.6%	36.0%
8 - 9	59.3%	60.0%

Minutes after 9:00 am	Feb, Mar-20	Jul-20
9 - 10	70.4%	68.0%
10 - 11	85.2%	80.0%
11 - 12	88.9%	88.0%
12 - 13	91.7%	92.0%
13 - 14	94.5%	96.0%
14 - 15	97.2%	100.0%
15 - 16	100.0%	-

3.3.5.3 Tasks_to_Lunch

Nurses do not have a scheduled time to have lunch, so this function returns the number of tasks done before the lunch break. The simulations generate a random number between 0 and 1, 0.18, for example. Based on Table 3.3, the nurse is ready to go to the lunch break after a number of tasks between 61 and 70, and a number of tasks between 71 and 80 in the Feb, Mar-20 and Jul-20 simulation models, respectively.

Table 3.3. Cumulative frequency for the number of tasks conducted before the lunch break.

Number of Tasks	Feb, Mar-20	Jul-20
41 - 50	3%	-
51 - 60	8%	6%
61 - 70	19%	9%
71 - 80	31%	25%
81 - 90	64%	56%
91 - 100	78%	81%
101 - 110	86%	91%
111 - 120	92%	97%
121 - 130	100%	98%
131 - 140	-	100%

3.3.5.4 Time_to_Handoff

The nurse does not do handoff at the end of the day at the same time every day. It will depend on if the next shift nurse is available for handoff. A good reason a next shift nurse is not available for handoff is that she is doing a handoff with another nurse. So, this function returns the exact time a nurse starts her handoff with the next shift nurse. Figure

3.15 outlines the cumulative frequency for nurses' time to start the handoff at the end of the day based on the time-study data. The simulations generate a random number between 0 and 1, 0.45 for example. Based on the time-study data, the handoff would start randomly from 7:11 to 7:12 pm and from 7:08 to 7:09 pm in the Feb, Mar-20 and Jul-20 simulation models, respectively.

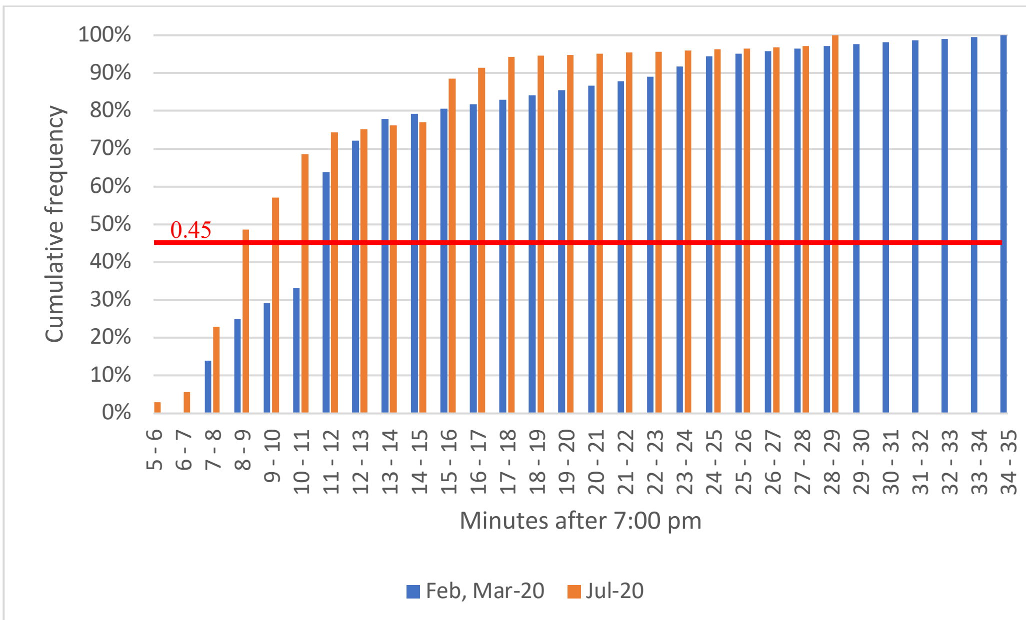


Figure 3.15. Cumulative frequency for the time the nurse starts handoff in the end of the day.

3.3.5.5 Events

The function Events has as input the shift's phase and does not return any value but calls for all Task_Events functions (see Section 3.3.5.5.1).

3.3.5.5.1 Task_Events

For every single possible task during a shift (see Appendix A), there is a Task_Events function, with the phase number as the input, for example O4_Events, that returns the number of tasks the nurse will carry out during a phase shift, in this case O4 (talking with other healthcare personnel). Figure 3.16 shows the frequency distribution of O4 activities as a function of the shift phase, which may be performed in all four phases and in both periods' simulation models. For instance, N3 task happens only in phase 0, some tasks only in phases 1 and 2 (N4, O5, O6, O7, O8, O9, O13, PC6, PC7, PC10, PC11, PC12, PC14, PC15, PC16, PC17, PC18, PC19, PS2, PS3, PS4), N2 only in phase 3, and others may take part in more than one phase (N1, N5, O1, 02, O3, O4, O10, O11, O12, O14, O15, PC1, PC2, PC3, PC4, PC5, PC8, PC9, PS1, V2, V2+PC1).

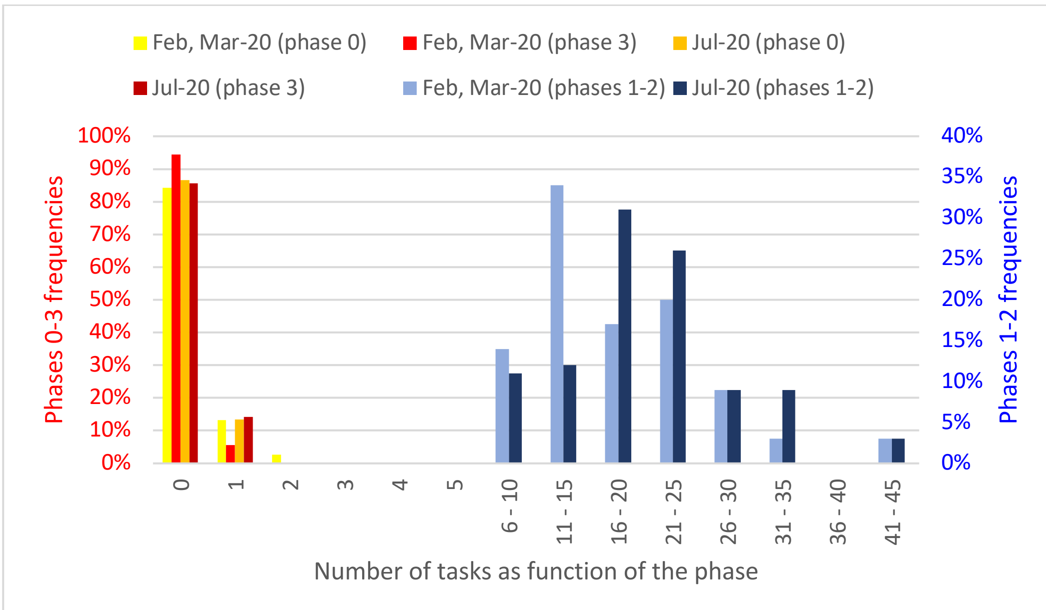


Figure 3.16. Frequency distribution for O4 activities as function of the shift phase.

3.3.5.6 Add_Events

The function Add_Events updates the scheduled number of all tasks in the simulation models to the closest integer to the mean number of that task, performed in a shift from the time-study dataset. For example, during July 2020 the mean observed tasks for PC9 is 5.771 in a shift, so the function Add_Events is going to update $a_{2\_4} = 6$.

3.3.5.7 Task_Duration

For every single possible task of a shift (Appendix A), there is a Task_Duration function associated to it, for example PC8_Duration, that returns the task duration in minutes whenever a task is conducted in the simulation models, in this case PC8 (Talking to Family). Figure 3.17 outlines the cumulative frequency for the PC8 duration based on the time-study data. The simulations generate a random number between 0 and 1, 0.3 for example. Based on the time-study data, PC8 will have a random time from 2 to 3 minutes and 1 to 2 minutes in the February to March 2020 and July 2020 simulation models, respectively.

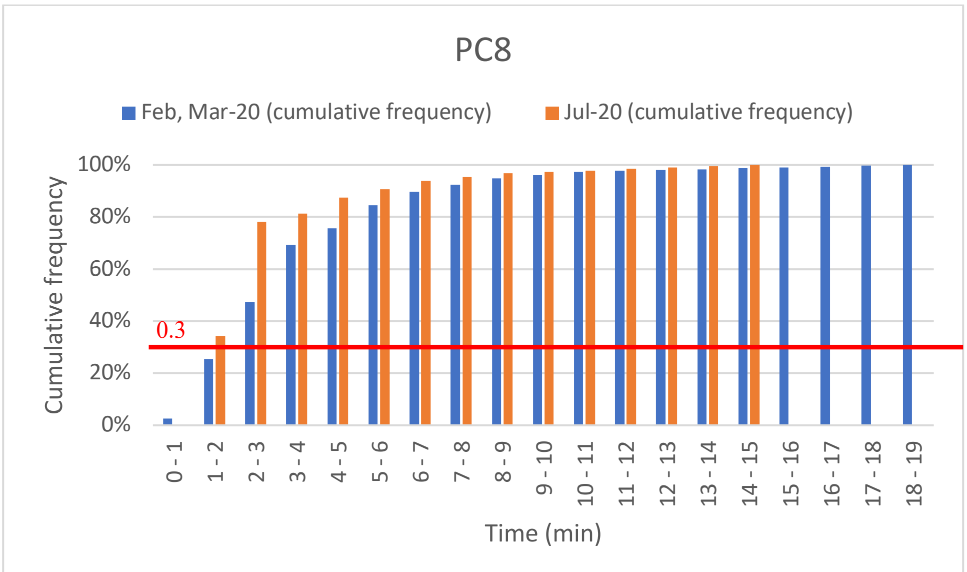


Figure 3.17. Cumulative frequency for PC8 duration.

3.3.5.8 Fatigue

Jaber *et al.* (2013) state that the way the human body accumulates fatigue remains an open research question to be addressed in the human physiology literature. However, they treated fatigue accumulation as an exponential function, also adopted in this study (see Equation (3.8).

$$F_i(t) = F_{i-1} + (1 - F_{i-1})\left(1 - e^{-\lambda_j t}\right), 0 < t \leq t_i \qquad (3.8)$$

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 shift "k".
$F_{i-1} =$ residual fatigue, accumulated after the previous task.
$F_0 = 0$.
$t_i =$ time to complete the task "i".

$j = \text{PC1, ..., PC19, O1, ..., O15, PS1, ..., PS4 (see Appendix A).}$
$\lambda_j = \text{the fatigue index for task "j".}$
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

$$x = i - 1 + \frac{t}{t_i}, 0 < t \leq t_i$$
$$F_i(x) = F_{i-1} + (1 - F_{i-1})\left(1 - e^{-\lambda_j (x-i+1)t_i}\right), i - 1 < x \leq i \tag{3.9}$$

For example, given that $i = 6, t_6 = 11.575 \text{ min}, F_5 = 0.46, \lambda_{PC1} = 0.0192$:
$F_6(x) = 0.46 + 0.54\left(1 - e^{-0.0192(x-5)11.575}\right), 5 < x \leq 6$

According to Givi *et al.* (2015), both the fatigue accumulation index and the recovery speed index were determined using a test. They use three levels for the fatigue and recovery indexes, low, medium, and fast. 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 for the high level, 4 hours for exhaustion.

In this study, for each task, the adopted fatigue/recovery indexes aim to represent the 6 ratings used by NASA TLX, mental demand, physical demand, temporal demand, performance, effort, and frustration, in three qualitative factors.

The present assessment tool was developed to define if an activity demands, is neutral to, or is invigorating in terms of mental demand, physical demand, and effort, a qualitative analyzes instead of the quantitative NASA-TLX's assessment. 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. Appendix A shows the adopted fatigue/recovery indexes for all nurse activities. It is worthwhile to mention that all tasks were analyzed with an expert support.

Finally, the fatigue range is from 0, in the beginning of the shift, to 1 (100%), and the Fatigue function returns the nurse accumulated fatigue level after conducting an activity.

3.3.5.9 Recovery

Konz (1998) 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 (3.10).

$$F_i(t) = F_{i-1}e^{-\mu_j t}, 0 \leq t \leq t_i \tag{3.10}$$

Where:
$i = 1, 2, \dots, n_k$, refers to the i^{th} task conduct 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 = N1, ..., N6. It refers to the task code (see Appendix A).
μ_j =the recovery index for task "j".

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

$$x = i - 1 + \frac{t}{t_i}, 0 < t \leq t_i$$
$$F_i(x) = F_{i-1}e^{-\mu_j(x-i+1)t_i}, i - 1 < x \leq i \tag{3.11}$$

For example, given that $i = 57, t_{57} = 32.531$ min, $F_{56} = 09, \mu_{N6} = 0.0192$:
$F_{57}(x) = 0.9e^{-0.0192(x-56)32.531}, 56 < x \leq 57$

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

3.4 Average Fatigue Level

Equation (3.12 is the general equation for calculating the average fatigue level during the shift. Depending on whether a task increases, does not affect, or decreases fatigue, its contribution for the shift average fatigue level is calculated using the Equations (3.13, (3.14, or (3.15 respectively.

$$F_{avg} = \frac{1}{n_k}\sum_{i=1}^{n_k}\int_{i-1}^{i} F_i(x)dx \tag{3.12}$$

$$\begin{aligned}\int_{i-1}^{i} F_i(x)dx &= \int_{i-1}^{i} \left[F_{i-1} + (1 - F_{i-1})\left(1 - e^{-\lambda_j(x-i+1)t_i}\right)\right]dx \\ &= \int_{i-1}^{i} \left[1 - (1 - F_{i-1})e^{-\lambda_j(x-i+1)t_i}\right]dx \\ &= 1 - \frac{(1 - F_{i-1})\left(1 - e^{-\lambda_j t_i}\right)}{\lambda_j t_i}\end{aligned} \tag{3.13}$$

$$\int_{i-1}^{i} F_i(x)dx = F_{i-1}, \text{ given } \lambda_j = 0 \tag{3.14}$$

$$\int_{i-1}^{i} F_i(x)dx = \int_{i-1}^{i} F_{i-1}e^{-\mu_j(x-i+1)t_i}dx = \frac{F_{i-1}}{\mu_j t_i}(1 - e^{-\mu_j t_i}) \tag{3.15}$$

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".
F_{i-1} = residual fatigue, accumulated after the previous task.
$F_0 = 0$.
j = PC1, ..., PC19, O1, ..., O15, PS1, ..., PS4, N1, ..., N6. (see Appendix A).
λ_j = the fatigue index for task "j".
μ_j = the recovery index for task "j".

Figure 3.18 shows an example of fatigue level outcome based on the Fatigue and Recovery functions. It also shows the nurse average fatigue level for that shift.

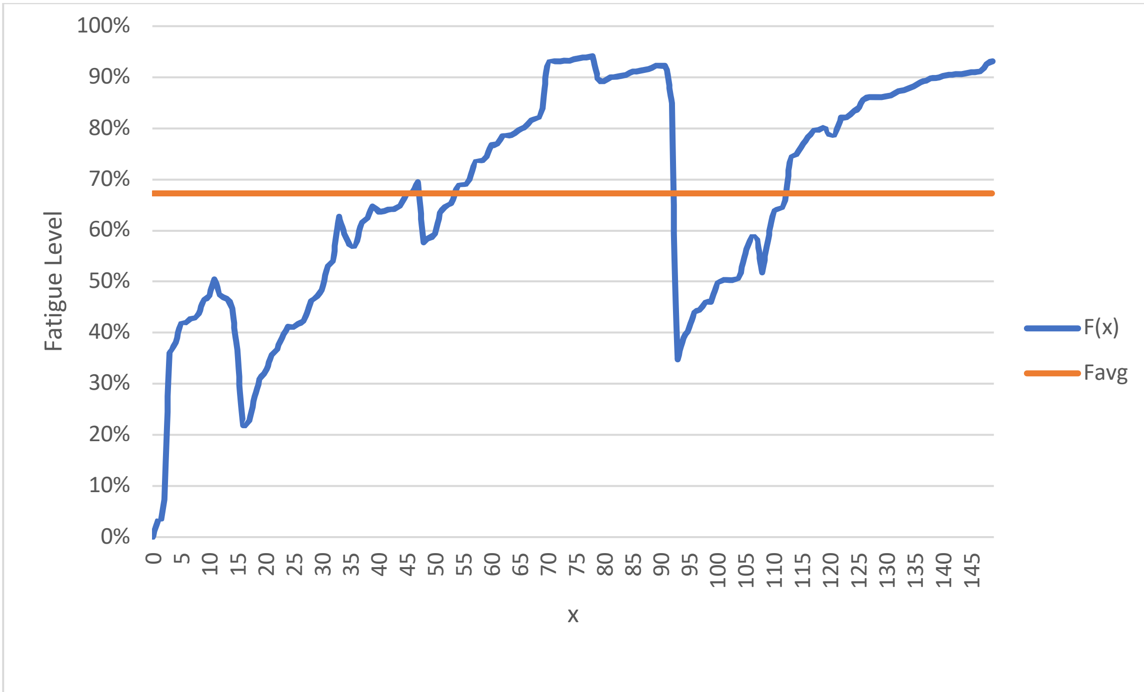


Figure 3.18. Fatigue and Recovery functions during a shift.

3.5 Comparing Observed with Simulated Data

The observed data in both periods was compared to the simulation outcomes using the RStudio software, using t-tests for task frequency and duration comparisons. R is an open-source software for statistical computing and graphics (Verzani, 2011). Kronthaler and Zöllner (2021) add that R can be understood as a platform with which the most diverse applications of data analysis are possible. However, besides the tools offered by the pure R, RStudio offers an appealing and modern interface, according to Kronthaler and Zöllner (2021).

3.6 Design of The Experiment

According to Montgomery (2017), a full-factorial design is the most efficient type of experiment when it involves two or more factors associated to a response. However, in this study, it will not use a factorial design with fixed level, instead the independent variables will variate randomly. This is approach is due to all or almost all independent variables are correlated to each other. Otherwise, suppose that a full-factorial design with fixed levels is chosen for this study. And now, it is time to simulate the run when all variables are in high level, but the shift still lasts in average 12 hours, then it is impossible to accommodate that.

The model-dependent variable is nurses' average fatigue level, and this study aims to analyze its pattern by simulated experiments varying all nursing tasks' frequencies and sequences randomly, the independent variables, in a screening experiment. From Appendix A, the tasks within the categories Primary Care, Peer Support, and Out-of-room Activities, except by PC10 and O6, the teaching activities, are used as the frequency independent variables. Besides the frequency independent variables, this study uses two sequence independent variables, number of task sequences prior to lunch (seq_0) and after lunch (seq_1). A task sequence lasts while a nurse is conducting any activity related to the patient care, be it inside or outside the patient room, is supporting a peer, or is talking with someone else about a patient clinical condition. Then, when the nurse goes to a break, that is, does any kind of non-valuable activity, the task sequence finishes. It is important to clarify that if in a shift a nurse conducts 100 tasks using 5 task sequences, it turns out in average 20 tasks/sequence. On the other hand, for the same 100 tasks, but using 10 task sequences, it turns out 10 tasks/sequence. So, for a 12-hour shift, the greater the number of task sequences, the greater the number of breaks between them.

For the experiment's accuracy, several adjustments were made. The three tasks performing procedure (PC3), patient care (PC4), and closed curtain (PC19) were combined in one new variable, called ***pc***. This adjustment is due to PC19 might be both PC3 or PC4, since the observer cannot identify it. Also, the tasks within the category peer support were combined in the variable, called ***ps***, as PS4 also refers to a closed curtain task. Finally, tasks that might happen in- or out-of-room were counted together, as PC9 and O11 (EMR charting) turn out ***emr***, PC11 and O2 (using ASCOM phone) turn out ***ascom***, PC7 and O3 (talking with a physician) turn out ***twp***, and PC8 and O5 (talking with patient's family) turn out ***twf***.

Each simulation model carried out 1,000 runs, and the simulated data were analyzed using JMP software, which turns out the response prediction expression (see Equation (3.16). JMP is a statistical software environment that enables scientists, engineers, and business analysts to make discoveries through data exploration (Jones and Sall, 2011). JMP offers several features for distribution analysis (including contingency tables, outlier analysis, and nonparametric statistics), and graphs (including contour, profile, and ternary charts), time series modeling, regression, logit analysis, cluster analysis, survival, design of experiments, and quality control (Altman, 2002).

All independent variables were standardized using the transformation in Equation (3.17). That transformation makes all independent variables have $\text{mean}=0$ and $\text{standard deviation}=1$, and the benefits of that are: $\hat{\beta}_0$ represents the average response and the estimated coefficients represent their variables' impact over the response, that is, the greater the coefficient, the larger the effect on the response.

$$\hat{F}_{avg} = \hat{\beta}_0 + \sum_{i=1}^{n} \hat{\beta}_i \, z_i, i = 1, 2, \dots, n \tag{3.16}$$

Where:
$\hat{F}_{avg}$ = estimated average fatigue level during a shift.
$\hat{\beta}_0$ = intercept (average response).
$\hat{\beta}_i$ = estimated coefficients for the main effects.
z_i = standardized independent variables.

$n =$ number of independent variables.

$$z_{i,r} = \frac{x_{i,r} - \bar{x}_i}{S_i} \tag{3.17}$$

Where:

$z_{i,r}$ = standardized variable z_i at run r.
$x_{i,r}$ = variable x_i at run r.
$\bar{x}_i$ = mean for variable x_i.
S_i = standard deviation for variable x_i.

CHAPTER 4: RESULTS

4.1 Task Frequencies

The simulation models were used to run 2 experiments, one for each period, and turned out the frequency for 40 different tasks, from the total of 46 (see Appendix A), 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 (V2), verbal report along with patient initial assessment (V2+PC1), waiting to give report to nurse (N2), and waiting to receive report from nurse (N3) activities were not compared. Also, staff meeting (morning huddle, O8) and lunch break (N6) activities were not compared, because they do not happen as a function of frequency distributions, but they depend on the nurse availability. They are considered binary events (they happen or not during a shift).

4.1.1 Comparing the Observed Data with the Simulation Outcomes for February to March 2020

In this section, the observed data in Feb, Mar-20 is compared to the simulation outcomes using the RStudio software. For a statistical level of 0.05, all simulated tasks present the same pattern of the observed data, so the simulation model for February to March 2020 has significant evidence that represents the nurses' workflow in terms of task frequency.

In order to illustrate the results regarding the comparison the observed and simulated data, Figure 4.1 shows the out-of-room EMR charting (O11) frequency distribution, the most frequent task during a shift. Figure 4.2 shows the comparison between the average number of out-of-room EMR charting, with a p-value of 0.309.

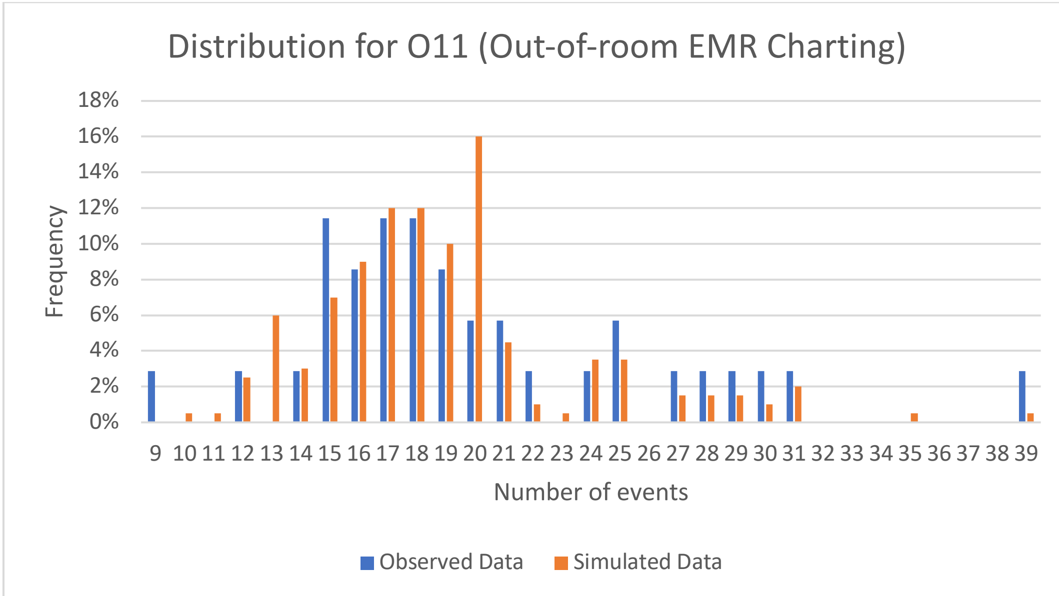


Figure 4.1. Frequency distribution for out-of-room EMR charting (O11).

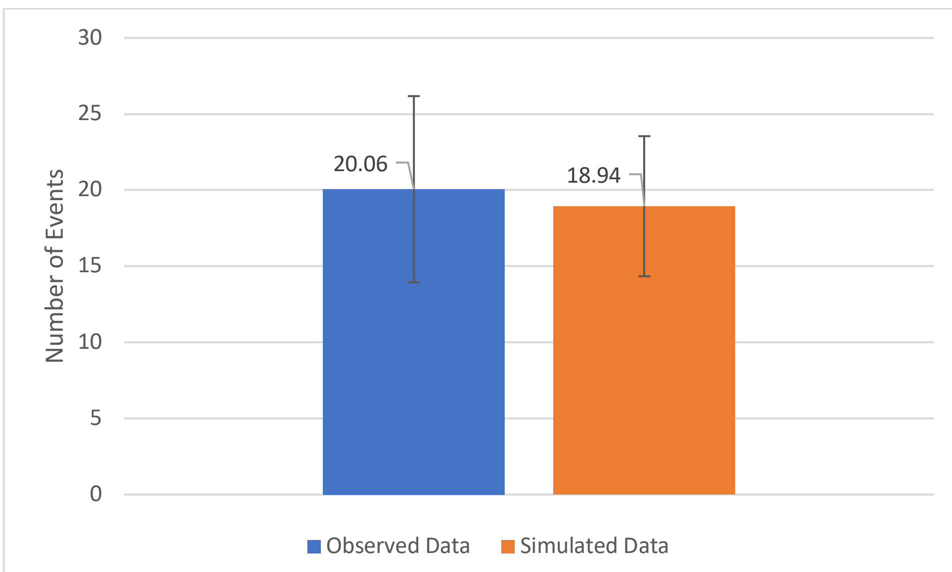


Figure 4.2. Average number of O11 (out-of-room EMR charting). P-value of 0.309.

4.1.2 Comparing the Observed Data with the Simulation Outcomes for July 2020

In this section, the observed data in Jul-20 is compared to the simulation outcomes using the RStudio software. For a statistical level of 0.05, all simulated tasks present the same pattern of the observed data, so the simulation model for July 2020 has significant evidence that represents the nurses' workflow in terms of task frequency.

In order to illustrate the results regarding the comparison the observed and simulated data, Figure 4.3 shows the out-of-room EMR charting (O11) frequency distribution, the most frequent task during a shift. Figure 4.4 shows the comparison between the average number of out-of-room EMR charting, with a p-value of 0.153.

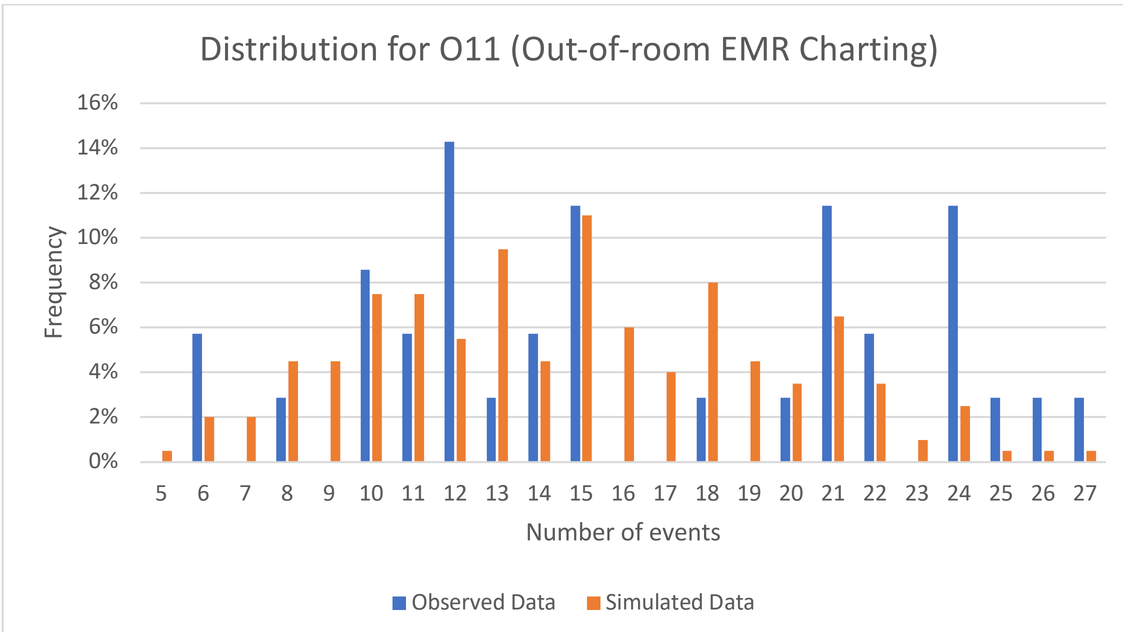


Figure 4.3. Frequency distribution for out-of-room EMR charting (O11).

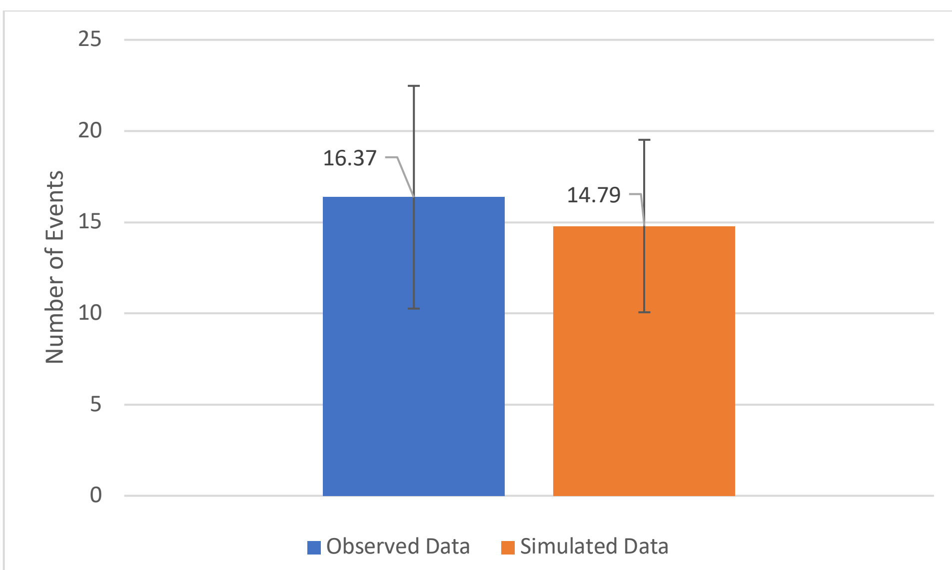


Figure 4.4. Average number of O11 (out-of-room EMR charting). P-value of 0.153.

4.2 Task Duration

To assess the task durations, from the table in Appendix A (list of all possible activities in nurse shift), the task durations were aggregated by categories: Verbal Report (V2 and V2+PC1), Primary Care (from PC1 to PC19), Out-of-room (from O1 to O15), Peer Support (from PS1 to PS4), and Non-nursing (from N1 to N6).

4.2.1 Comparing the Observed Data with the Simulation Outcomes for February to March 2020

In this section, the observed data from February to March 2020 is compared to the simulation outcomes (200 runs) using the RStudio software. Table 4.1 shows the statistical t-tests, and for a statistical level of 0.05, all simulated category durations present the same pattern of the observed data, so the simulation model for February to March 2020 has significant evidence that represents the nurses' workflow in terms of task duration. Figure 4.5 also represents the comparison between the observed and simulated proportion of time nurses spend on task categories.

Table 4.1. Comparison between observed and simulated data in terms of task category proportions (Feb, Mar-20).

Category	Sample Type	Mean	SD	Statistic	p
Verbal Report	Observed	4.3%	1.5%	-0.211	0.833
	Simulated	4.3%	1.8%		
Primary Care	Observed	35.1%	10.3%	-0.702	0.487
	Simulated	36.3%	6.2%		
Out-of-room	Observed	35.6%	6.2%	0.418	0.676
	Simulated	35.1%	5.9%		
Peer Support	Observed	6.9%	3.5%	-0.646	0.519
	Simulated	7.3%	3.4%		
Non-nursing	Observed	18.2%	9.0%	0.825	0.414
	Simulated	16.9%	5.1%		

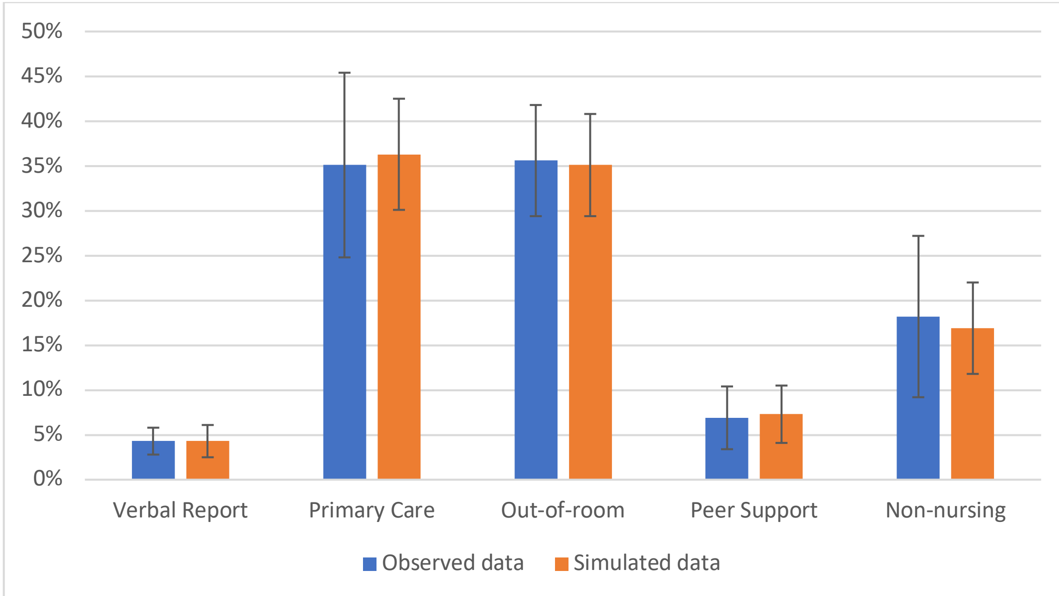


Figure 4.5. Proportion of time that nurses spend on task categories (Feb, Mar-20).

4.2.2 Comparing the Observed Data with the Simulation Outcomes for July 2020

In this section, the observed data from July 2020 is compared to the simulation outcomes (200 runs) using the RStudio software. Table 4.2 shows the statistical t-tests, and for a statistical level of 0.05, all simulated category durations present the same pattern of the observed data, so the simulation model for July 2020 has significant evidence that represents the nurses' workflow in terms of task duration. Figure 4.6 also represents the comparison between the observed and simulated proportion of time nurses spend on task categories.

Table 4.2. Comparison between observed and simulated data in terms of task category proportions (Jul-20).

Category	Sample Type	Mean	SD	Statistic	p
Verbal Report	Observed	5.1%	1.7%	-1.666	0.097
	Simulated	5.6%	1.8%		
Primary Care	Observed	34.2%	11.4%	0.298	0.767
	Simulated	33.6%	7.6%		
Out-of-room	Observed	34.8%	6.9%	-0.062	0.951
	Simulated	34.8%	6.7%		
Peer Support	Observed	6.7%	4.8%	0.411	0.682
	Simulated	6.4%	3.5%		
Non-nursing	Observed	19.3%	7.6%	-0.228	0.820
	Simulated	19.6%	6.3%		

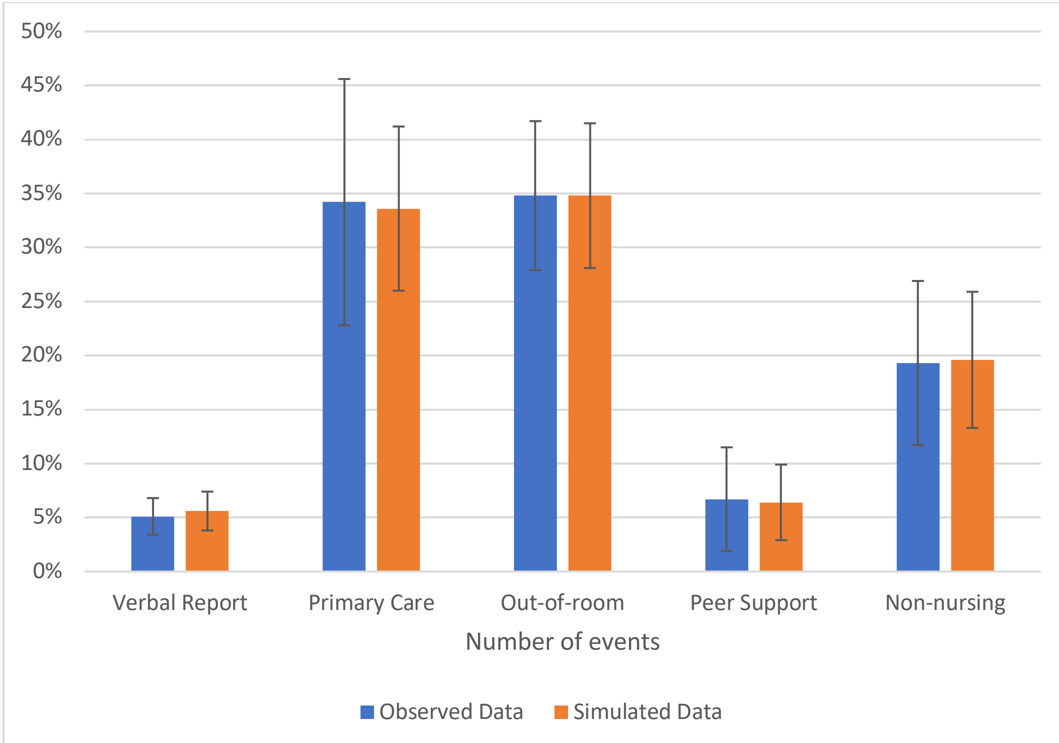


Figure 4.6. Proportion of time that nurses spend on task categories (Jul-20).

4.3 Average Fatigue Level

Since both simulation models are validated, that is, they represent the time-study dataset, two experiments, for simulating the average fatigue level reached during a shift, were conducted with 1,000 runs for each period. This number of runs is significant enough to use the significance level of 0.01 and do not increase the probability of mistakenly conclude that both periods present the same average fatigue level patterns, when actually they do not. Table 4.3 shows that the average fatigue level is different for between the periods of interest ($\alpha = 0.01$), and that Feb, Mar-20 shifts turned out a little bit more fatigue than the Jul-20 ones.

Table 4.3. Comparison between simulated average fatigue level for Feb, Mar-20 and Jul-20 models.

Period	Average Fatigue Level	SD	Statistic	p
Feb, Mar-20	0.636	0.070	2.758	**0.006**
Jul-20	0.627	0.069		

4.3.1 Average Fatigue Level Screening

Although the models are different in their average fatigue level, they have some similarities. They have in common that $\boldsymbol{seq_0}$, $\boldsymbol{seq_1}$, ***pc***, and ***ps*** variables are significant in both periods, outstanding as the most important drivers of fatigue for nurses.

4.3.1.1 Feb, Mar-20 Model

Equation (4.1) is the predicted average fatigue level as function of the most significant independent variables ($p = 0.01$).

$$\hat{F}_{avg} = 0.636 - 0.040z_{seq_1} - 0.039z_{seq_0} + 0.010z_{pc} + 0.009z_{emr} + 0.008z_{ps} + 0.005z_{twf} + 0.004z_{pc1} \quad (4.1)$$

Table 4.4 presents the most significant independent variables for the significance level of 0.01, in order of significance.

Table 4.4. Standardized parameter estimates (Feb, Mar-20 model).

Variable	Confidence Interval	P
$\boldsymbol{seq_1}$	[-0.041, -0.038]	< 0.001
$\boldsymbol{seq_0}$	[-0.041, -0.038]	< 0.001
pc	[0.009, 0.012]	< 0.001
emr	[0.007, 0.010]	< 0.001
ps	[0.007, 0.009]	< 0.001
twf	[0.003, 0.006]	0.0008
$\boldsymbol{pc_1}$	[0.003, 0.006]	0.0024

Table 4.5 shows the simulated outcomes for the most significant independent variables for the model. From the table, for example, the model simulated in average 10.48 task sequences after lunch ($\boldsymbol{seq_1}$) and 23.211 ***pc*** tasks.

Table 4.5. Simulated outcomes (Feb, Mar-20 model).

Variable	Mean	Standard Deviation
$\boldsymbol{seq_1}$	10.480	5.721
$\boldsymbol{seq_0}$	8.847	4.799
pc	23.211	5.377
emr	25.289	6.541
ps	10.630	4.206

Variable	Mean	Standard Deviation
twf	2.843	2.256
pc_1	0.985	1.309

Also, Equation (4.1 tells that, for the variable seq_1, an increment of 1 standard deviation, that is, 5.721 task sequences after lunch (Table 4.5), should decrease the average fatigue level in 0.04, or it may be as great as 0.041 or as low as 0.038 (Table 4.4). For the variable seq_0, an increment of 1 standard deviation, that is, 4.799 task sequences before lunch, should decrease the average fatigue level in 0.039, or it may be as great as 0.041 or as low as 0.038. For the variable ***pc***, an increment of 1 standard deviation, that is, 5.377 tasks, be it performing procedure (PC3), patient care (PC4), or closed curtain (PC19), should increase the average fatigue level in 0.01, or it may be as low as 0.009 or as great as 0.012. For the variable ***emr***, an increment of 1 standard deviation, that is, 6.541 in EMR charting, be it conduct inside patient room (PC9) or outside patient room (O11), should increase the average fatigue level in 0.009, or it may be as low as 0.007 or as great as 0.010. For the variable ***ps***, an increment of 1 standard deviation, that is 4.206 in peer support tasks, be it assisting in patient care (PS1), assisting in nurse-led procedure (PS2), assisting in physician-led procedure (PS3), or assisting in a closed curtain task (PS4), should increase the average fatigue level in 0.008, or it may be as low as 0.007 or as great as 0.009. For the variable ***twf***, an increment of 1 standard deviation, that is, 2.256 in the number of times talking with patients' families, be it inside a patient room (PC8) or outside a patient room (O5), should increase the average fatigue level in 0.005, or it may be as low as 0.003 or as great as 0.006. For the variable pc_1, an increment of 1 standard deviation, that is, 1.309 in focused assessment should increase the average fatigue level in 0.004, or it may be as low as 0.003 or as great as 0.006.

4.3.1.2 Jul-20 Model

Equation (4.2 is the predicted average fatigue level as function of the most significant independent variables ($p = 0.01$).

$$\hat{F}_{avg} = 0.627 - 0.036z_{seq_1} - 0.033z_{seq_0} + 0.018z_{pc} + 0.012z_{ps} + 0.006z_{pc12} \quad (4.2)$$

Table 4.6 presents the most significant independent variables for the significance level of 0.01, in order of significance.

Table 4.6. Standardized parameter estimates (Jul-20 model).

Variable	Confidence Interval	P
seq_1	[-0.037, -0.034]	< 0.001
seq_0	[-0.035, -0.031]	< 0.001
pc	[0.016, 0.019]	< 0.001
ps	[0.010, 0.013]	< 0.001
pc_{12}	[0.005, 0.008]	< 0.001

Table 4.7 shows the simulated outcomes for the most significant independent variables for the model. From the table, for example, the model simulated in average 10.48 task sequences after lunch (seq_1) and 23.211 ***pc*** tasks.

Table 4.7. Simulated outcomes (Jul-20 model).

Variable	Mean	Standard Deviation
seq_1	7.206	5.422
seq_0	13.900	5.899
pc	20.841	5.315
ps	10.201	4.598
pc_{12}	0.659	0.870

Also, Equation (4.2 tells that, for the variable seq_1, an increment of 1 standard deviation, that is, 5.422 task sequences after lunch (Table 4.7), should decrease the average fatigue level in 0.036, or it may be as great as 0.037 or as low as 0.034 (Table 4.6). For the variable seq_0, an increment of 1 standard deviation, that is, 5.899 task sequences before lunch, should decrease the average fatigue level in 0.033, or it may be as great as 0.035 or as low as 0.031. For the variable ***pc***, an increment of 1 standard deviation, that is, 5.315 tasks, be it performing procedure (PC3), patient care (PC4), or closed curtain (PC19), should increase the average fatigue level in 0.018, or it may be as low as 0.016 or as great as 0.019. For the variable ***ps***, an increment of 1 standard deviation, that is 4.598 in peer support tasks, be it assisting in patient care (PS1), assisting in nurse-led procedure (PS2), assisting in physician-led procedure (PS3), or assisting in a closed curtain task (PS4), should increase the average fatigue level in 0.012, or it may be as low as 0.01 or as great as 0.013. For the variable $\boldsymbol{pc_{12}}$, an increment of 1 standard deviation, that is, 0.87 in the number of patient transportation tasks should increase the average fatigue level in 0.006, or it may be as low as 0.005 or as great as 0.008.

4.4 Comparing the Key Factors' Patterns in the Observed Dataset

Both the number of times a sequence of tasks is conducted without a break, prior to or after lunch, are the most significant fatigue drivers in both periods. Although the models do not show how many tasks are performed during a sequence, the total number of tasks conducted during a shift may give a clue of this, that is, the greater the total number of tasks performed, the greater should be the number of tasks within a sequence. So, when the total number of tasks conducted in each period is compared, Table 4.8 shows that during July 2020, the total number of performed tasks in average decreased 9.5% in comparison to February and March 2020.

The number of patient care or procedures conducted during a shift is a significant fatigue driver in both periods and the differences presented in the dataset are not significant for the significance level of 0.05. Peer support activities are other type of tasks that are important fatigue drivers in both periods and do not present significant differences between periods for the significance level of 0.05 (see Table 4.8). The exception here is the number of patient transportation activities that do not present significant differences between periods ($\alpha = 0.05$), but it is only a significant fatigue driver for July 2020, which requires further investigation.

On the other hand, the number of EMR charting tasks are relevant only for the Feb, Mar-20 model, and when the periods' patterns are compared to each other, it is possible to identify that the number of EMR charting decreased 16.5% in average during July 2020 in comparison to February and March 2020. Moreover, it is possible to identify the same pattern in the number of times nurses used to talk with patients' families, that decreased 74.3% in average, and the number of conducted initial assessments, that decreased 72.2% in average, during July 2020 in comparison to February and March 2020 (see Table 4.8).

Table 4.8. Comparison of the nurses' fatigue key drivers between periods.

Factor	Period	Mean	SD	Statistic	P[3]
Total number of activities during the shift	Feb, Mar-20 Jul-20	154.457 139.800	22.543 19.560	2.905	**0.005***
Conducting a procedure or patient care (PC3 + PC4 + PC19)	Feb, Mar-20 Jul-20	23.657 20.229	7.487 7.113	1.964	0.054
EMR charting (PC9 + O11)	Feb, Mar-20 Jul-20	25.829 21.571	6.913 7.808	2.415	**0.018***
Peer support (PS1 + PS2 + PS3 + PS4)	Feb, Mar-20 Jul-20	10.686 9.800	5.492 5.965	0.646	0.520
Talking with patient's family (PC8 + O5)	Feb, Mar-20 Jul-20	2.886 0.743	2.988 1.400	3.842	**<0.001***
Initial assessment (PC1)	Feb, Mar-20 Jul-20	0.972 0.270	1.320 0.508	2.983	**0.005***
Transport/prepare to transport a patient (PC12)	Feb, Mar-20 Jul-20	0.943 0.543	0.998 0.980	1.691	0.095

4.4.1 Comparing Patient Transportation Duration between Periods

Although the number of patient transportation activities does not present significant differences between periods ($\alpha = 0.05$), as shown in Table 4.8, during July 2020, that type

[3] P-values presenting an "*" are significant for $\alpha = 0.05$.

of activity used to be in average more than 3 times longer than during February and March 2020 (see Table 4.9).

Table 4.9. Comparison of patient transportation duration between periods.

Period	Mean (min)	SD (min)	Statistic	P
Feb, Mar-20	9.4	12.6	-2.259	**0.035**
Jul-20	31.3	41.3		

4.5 Key Factors in Simulation Outcomes

Two more experiments were run in order to investigate the differences in the fatigue key factors between the two simulation model periods. They were conducted with 1,000 runs for each period, and it was used the significance level of 0.01, which do not increase the probability of mistakenly conclude that both periods present the same pattern, when actually they do not.

4.5.1 Simulated Time Spent in the Seven Main Task Categories

Table 4.10 compares the simulated outcomes for the seven main task categories in the models. From the table below, it is possible to note that during February and March 2020, nurses spent more time in in-room and out-of-room activities, similar time in peer support activities between periods, while during July 2020, they spent more time in handoffs, patient clinical processes' conversations, and non-nursing activities.

Table 4.10. Comparing the seven main task categories between periods.

Factor	Period	Mean Duration/shift (min)	SD (min)	Statistic	P
Handoff	Feb, Mar-20	32.549	14.101	-11.931	**<0.001**
	Jul-20	40.150	14.386		
In-room Activities	Feb, Mar-20	278.444	45.257	9.115	**<0.001**
	Jul-20	259.197	53.721		
Out-of-room Activities	Feb, Mar-20	135.434	34.678	15.435	**<0.001**
	Jul-20	112.019	33.144		
Peer Support Activities	Feb, Mar-20	52.602	23.729	2.107	0.035
	Jul-20	50.155	28.040		
Patient Clinical Processes' Conversations	Feb, Mar-20	100.978	28.299	-20.871	**<0.001**
	Jul-20	131.350	36.286		
Teaching Residents/Students	Feb, Mar-20	9.063	19.681	-8.108	**<0.001**
	Jul-20	16.486	21.238		

Factor	Period	Mean Duration/shift (min)	SD (min)	Statistic	P
Non-nursing Activities	Feb, Mar-20 Jul-20	131.318 139.559	40.688 41.517	-4.483	**<0.001**

Figure 4.7 shows the outcomes of Table 4.10 in a graph with vertical bars.

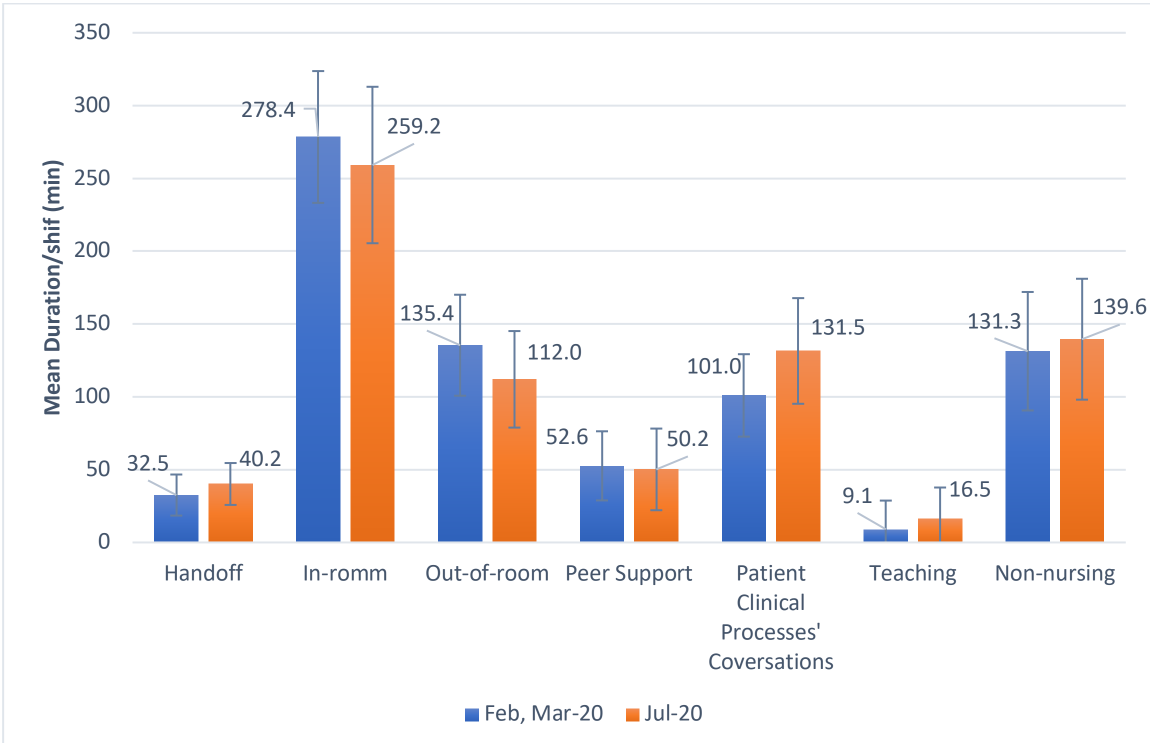


Figure 4.7. Comparing the seven main task categories between periods.

4.5.2 Simulated Time for Performing Procedure or Patient Care

Table 4.11 compares the simulated outcomes for the total duration of performing procedure or patient care (PC3 + PC4 + PC19), described by the variable ***pc.*** During the periods, the time spent in those type of activities is not statistically different.

Table 4.11. Comparing the duration of procedures and patient care activities between periods.

Period	Mean Duration/shift (min)	SD (min)	Statistic	P
Feb, Mar-20	139.777	39.858	1.261	0.208
Jul-20	137.378	45.083		

Although, PC3, PC4, and PC19 were put together in the models, because it is impossible to determine which task PC19 (unknow, closed curtain) really is, Table 4.12

shows the simulated frequency distribution for the variable ***pc,*** comparing both periods, and the fatigue indexes used in the simulation models.

Table 4.12. Simulated frequency distribution for the variable ***pc*** (PC3 + PC4 + PC19).

Factor	Fatigue Index	Period	Number of Tasks/shift	SD	Statistic	P
PC3 (Procedure)	High	Feb, Mar-20	10.880	3.823	3.084	0.017
		Jul-20	9.640	4.208		
PC4 (Patient Care)	Medium	Feb, Mar-20	11.650	4.063	19.332	**<0.001**
		Jul-20	5.030	2.635		
PC19 (Closed Curtain)	High	Feb, Mar-20	1.165	1.442	-11.579	**<0.001**
		Jul-20	4.020	3.175		

4.5.3 Simulated Time for EMR Charting

Table 4.13 compares the simulated outcomes for the total duration of EMR charting activities (O11 + PC9), described by the variable ***emr.*** During the periods, the time spent in those type of activities was 12% greater during February and March 2020 than during July 2020.

Table 4.13. Comparing the duration of EMR charting activities between periods.

Period	Mean Duration/shift (min)	SD (min)	Statistic	P
Feb, Mar-20	129.646	36.826	8.554	**<0.001**
Jul-20	115.573	36.750		

4.5.4 Simulated Time for Peer Support Activities

Although, PS1, PS2, PS3, and PS4 were put together in the models, because it is impossible to determine which task PS4 (unknow, closed curtain) really is, Table 4.14 shows the simulated frequency distribution for the variable ***ps,*** comparing both periods, and the fatigue indexes used in the simulation models.

Table 4.14. Simulated frequency distribution for the variable ***ps*** (PS1 + PS2 + PS3 + PS4).

Factor	Fatigue Index	Period	Number of Tasks/shift	SD	Statistic	P
PS1 (Assisting in Patient Care)	Medium	Feb, Mar-20	5.660	3.405	10.771	**<0.001**
		Jul-20	2.625	2.070		
PS2 (Assisting in Nurse-led Procedure)	High	Feb, Mar-20	4.295	2.625	-1.358	0.175
		Jul-20	4.770	4.192		
	High	Feb, Mar-20	0.235	0.425	1.100	0.272

Factor	Fatigue Index	Period	Number of Tasks/shift	SD	Statistic	P
PS3 (Assisting in Physician-led Procedure)		Jul-20	0.180	0.565		
PS4 (Closed Curtain)	High	Feb, Mar-20 Jul-20	0.630 1.685	0.852 1.679	-7.922	**<0.001**

4.5.5 Simulated Time for Initial Assessment Tasks

Patients' initial assessment may be conducted in two ways: In the beginning of shift, along with the shift handoff (V2 + PC1), or during the regular shift (PC1), while the shift has already begun. The variable $\boldsymbol{pc_1}$ takes account only for the second case, during the regular shift. Table 4.15 shows that nurses used to take much more time in regular initial assessments during February and March 2020.

Table 4.15. Comparing the duration of patients' initial assessment between periods.

Factor	Period	Mean Duration/shift (min)	SD (min)	Statistic	P
Initial Assessment (PC1)	Feb, Mar-20 Jul-20	5.676 1.237	8.052 2.229	16.767	**<0.001**

4.6 Sensitivity Analysis

Recalling that $\boldsymbol{seq_0}$, $\boldsymbol{seq_1}$, $\boldsymbol{pc}$, and $\boldsymbol{ps}$ variables are the most important drivers of fatigue for nurses in both models, Feb, Mar-20 and Jul-20. Also, $\boldsymbol{seq_0}$ and $\boldsymbol{seq_1}$ are not controllable, that is, they will depend on how many tasks a nurse will conduct during the shift. The greater the total number of tasks, the less the number of task sequences.

Besides, it is important to recall that all simulation models' independent variables were standardized using the transformation in Equation (3.17). That transformation makes all independent variables have $\text{mean}=0$ and $\text{standard deviation}=1$. Then, here in the sensitivity analysis section, new experiments were run varying the variables $\boldsymbol{pc}$ and $\boldsymbol{ps}$ in order to understand the effects on the dependent variable, F_{avg}.

Finally, for a better understanding of the variable effects on the models, Equations (4.1 and (4.2 are rewritten using their variables without the standardization.

4.6.1 Feb, Mar-20 Model

Applying the transformation from Equation (3.17), Equation (4.1 may be written as:

$$\hat{F}_{avg} = 0.636 - 0.040\frac{(seq_1 - 10.5)}{5.7} - 0.039\frac{(seq_0 - 8.8)}{4.8} + 0.010\frac{(pc - 23.2)}{5.4} + 0.009\frac{(emr - 25.3)}{6.5} + 0.008\frac{(ps - 10.6)}{4.2} + 0.005\frac{(twf - 2.8)}{2.3} + 0.004\frac{(pc_1 - 1)}{1.3} \tag{4.3}$$

Table 4.16 shows different scenarios of the key fatigue drivers, varying the variables ***pc*** and ***ps*** in steps about 1 standard deviation, from -3 to +3, and the average fatigue level from the simulation outcomes. Besides, Table 4.16 also shows that an (a) increase (decrease) in ***pc*** or ***ps*** implies less (more) task sequences and less (more) other task types.

Table 4.16. Impact on the model outcomes due to changes in ***pc*** and ***ps*** (Feb, Mar-20).

Scenario	Independent Variables (Mean, SD)							Average Fatigue Level
	seq_1	seq_0	pc	emr	ps	twf	pc_1	
Normal shift	**(10.5, 5.7)**	**(8.8, 4.8)**	**(23.2, 5.4)**	**(25.3, 6.5)**	**(10.6, 4.2)**	**(2.8, 2.3)**	**(1.0, 1.3)**	**Mean: 63.6% SD: 7.0%**
-70.3% of *pc* (-3SD)	(13.2, 5.8)	(9.7, 5.2)	(6.9, 5.1)	(28.9, 6.4)	(13.1, 4.8)	(3.8, 2.3)	(1.0, 1.3)	Mean: 58.2% SD: 7.0%
-47.4% of *pc* (-2SD)	(12.5, 5.9)	(9.2, 5.1)	(12.2, 5.4)	(27.6, 6.4)	(12.4, 4.5)	(3.5, 2.4)	(1.0, 1.3)	Mean: 59.8% SD: 7.0%
-23.7% of *pc* (-1SD)	(11.4, 5.9)	(8.9, 4.9)	(17.7, 5.5)	(26.3, 6.6)	(11.8, 4.7)	(3.2, 2.4)	(1.0, 1.3)	Mean: 61.9% SD: 6.8%
+23.7% of *pc* (+1SD)	(9.3, 5.4)	(8.5, 4.5)	(28.7, 5.5)	(23.8, 6.6)	(10.3, 4.6)	(2.7, 2.4)	(1.0, 1.3)	Mean: 65.3% SD: 6.7%
+47.8% of *pc* (+2SD)	(8.2, 5.2)	(8.3, 4.5)	(34.3, 5.9)	(22.3, 6.2)	(9.4, 4.5)	(2.5, 2.3)	(1.0, 1.3)	Mean: 66.9% SD: 6.3%
+67.2% of *pc* (+3SD)	(7.6, 4.8)	(8.0, 4.3)	(38.8, 6.4)	(21.3, 6.0)	(8.9, 4.3)	(2.3, 2.2)	(1.0, 1.3)	Mean: 68.2% SD: 6.2%
-100% of *ps*	(11.5, 5.7)	(9.6, 5.0)	(25.0, 5.5)	(26.9, 6.5)	(0.0, 0.0)	(3.3, 2.4)	(1.0, 1.3)	Mean: 61.0% SD: 6.9%
-81.1% of *ps* (-2SD)	(11.2, 5.7)	(9.3, 5.0)	(24.5, 5.7)	(26.6, 6.5)	(2.0, 3.2)	(3.3, 2.4)	(1.0, 1.3)	Mean: 61.6% SD: 6.9%
-41.5% of *ps* (-1SD)	(11.0, 5.8)	(9.3, 5.0)	(23.9, 5.4)	(26.1, 6.7)	(6.2, 4.1)	(3.0, 2.3)	(1.0, 1.3)	Mean: 62.2% SD: 7.0%

Scenario	Independent Variables (Mean, SD)							Average Fatigue Level
	seq_1	seq_0	pc	emr	ps	twf	pc_1	
+40.6% of *ps* (+1SD)	(10.1, 5.5)	(8.6, 4.5)	(22.6, 5.3)	(24.4, 6.4)	(14.9, 4.2)	(2.7, 2.2)	(1.0, 1.3)	Mean: 64.7% SD: 6.6%
+82.1% of *ps* (+2SD)	(9.3, 5.5)	(8.1, 4.3)	(21.5, 5.4)	(22.6, 6.1)	(19.3, 4.8)	(2.5, 2.3)	(0.9, 1.2)	Mean: 67.8% SD: 6.4%
+117.0% of *ps* (+3SD)	(8.9, 5.4)	(7.7, 4.1)	(21.2, 5.5)	(21.9, 6.1)	(23.0, 5.1)	(2.6, 2.4)	(0.9, 1.2)	Mean: 69.3% SD: 6.0%

4.6.2 Jul-20 Model

Applying the transformation from Equation (3.17), Equation (4.2 may be written as:

$$\hat{F}_{avg} = 0.627 - 0.036\frac{(seq_1 - 7.2)}{5.4} - 0.033\frac{(seq_0 - 13.9)}{5.9} + 0.018\frac{(pc - 20.8)}{5.3} + 0.012\frac{(ps - 10.2)}{4.6} + 0.006\frac{(pc_{12} - 0.7)}{0.9} \tag{4.4}$$

Table 4.17 shows different scenarios of the key fatigue drivers, varying the variables ***pc*** and ***ps*** in steps about 1 standard deviation, from -3 to +3, and the average fatigue level from the simulation outcomes. Besides, Table 4.17 also shows that an (a) increase (decrease) in ***pc*** or ***ps*** implies less (more) task sequences and less (more) other task types.

Table 4.17. Impact on the model outcomes due to changes in ***pc*** and ***ps*** (Jul-20).

Scenario	Independent Variables (Mean, SD)					Average Fatigue Level
	seq_1	seq_0	pc	ps	pc_{12}	
Normal shift	**(7.2, 5.4)**	**(13.9, 5.9)**	**(20.8, 5.3)**	**(10.2, 4.6)**	**(0.7, 0.9)**	**Mean: 62.7% SD: 6.9%**
-78.4% of *pc* (-3SD)	(8.2, 5.9)	(15.5, 6.0)	(4.5, 4.4)	(12.5, 4.5)	(1.0, 0.8)	Mean: 56.9% SD: 7.1%
-53.4% of *pc* (-2SD)	(7.9, 5.8)	(14.8, 5.9)	(9.7, 5.6)	(11.9, 4.6)	(0.9, 0.9)	Mean: 59.1% SD: 7.1%
-27.9% of *pc* (-1SD)	(7.4, 5.5)	(14.2, 5.8)	(15.0, 5.5)	(11.2, 4.8)	(0.8, 0.9)	Mean: 61.2% SD: 7.0%
+25.5% of *pc* (+1SD)	(6.1, 4.7)	(12.7, 5.1)	(26.1, 5.2)	(9.3, 4.5)	(0.4, 0.7)	Mean: 67.4% SD: 6.3%
+53.4% of *pc* (+2SD)	(5.3, 4.2)	(12.0, 5.0)	(31.9, 5.8)	(8.6, 4.4)	(0.4, 0.7)	Mean: 71.4% SD: 5.8%
+67.2% of *pc* (+3SD)	(4.7, 3.8)	(11.4, 4.7)	(37.2, 6.9)	(7.9, 4.2)	(0.3, 0.6)	Mean: 75.3% SD: 5.2%
-100% of *ps*	(7.4, 5.6)	(14.7, 5.7)	(21.8, 5.2)	(0.0, 0.0)	(0.8, 0.9)	Mean: 60.5% SD: 6.8%
-89.2% of *ps* (-2SD)	(7.4, 5.5)	(14.5, 5.7)	(21.7, 5.2)	(1.1, 1.9)	(0.8, 0.9)	Mean: 60.7% SD: 6.7%

Scenario	Independent Variables (Mean, SD)					Average Fatigue Level
	seq_1	seq_0	pc	ps	pc_{12}	
-37.3% of *ps* (-1SD)	(7.2, 5.4)	(13.9, 5.5)	(21.2, 5.2)	(6.4, 4.3)	(0.7, 0.9)	Mean: 62.1% SD: 6.9%
+43.1% of *ps* (+1SD)	(6.7, 4.9)	(12.6, 5.2)	(19.9, 5.4)	(14.6, 4.8)	(0.6, 0.9)	Mean: 65.9% SD: 6.6%
+94.1% of *ps* (+2SD)	(6.3, 4.7)	(12.1, 4.8)	(19.3, 5.2)	(19.8, 5.1)	(0.5, 0.9)	Mean: 68.4% SD: 6.5%
+133.3% of *ps* (+3SD)	(6.0, 4.4)	(11.6, 4.6)	(18.7, 5.2)	(23.8, 5.4)	(0.5, 0.9)	Mean: 70.0% SD: 6.0%

4.6.3 Comparing the Scenarios

The first conducted test was to investigate if the different scenarios impact the simulated average fatigue level. Table 4.18 shows that the samples have different variances, turning out the Welch's test as suitable for testing those.

Table 4.18. Homogeneity of variances test (Levene's).

	F	df1	df2	p-value
Average Fatigue Level	8.792	25	25,774	**<0.001**

Table 4.19 shows that there is at least one pair of different scenarios of key independent variables.

Table 4.19. One-way Analysis of Variance.

	Method	F	df1	df2	p-value
Average Fatigue Level	Welch's	527.892	25	9,259.079	**<0.001**

Then, post hoc tests are required to identify the nature of the differences. The objectives of these post hoc tests are to identify significant differences between pairs of scenarios while maintaining acceptable levels of Type I error (the probability of concluding that the samples are different, when they actually are not). For example, if instead controlling the overall Type I error after two consecutive Student's t-tests, for a significance level of 0.01, the real probability of a nonsignificant result would be $0.99x0.99 = 0.9801$ and the new Type I error would be $1 - 0.9801 = 0.0199$. Although it still represents a low significance level, this study deals with 26 different scenarios, making 325 different combinations of paired tests, with a new Type I error of $1 - (0.99)^{325} = 0.96$, that is, the conclusion would be that the scenarios are all different for the average fatigue level.

So, this study used the Games-Howell method for the post hoc comparisons. Figure 4.8, a summary of the results of those comparisons, has the following interpretations:

Regarding the Feb, Mar-20 model, the scenario $\boldsymbol{ps + 1Std\ Dev}$ does not imply significant difference to the normal shift. The further increments in ***ps*** are all significant different in the Feb, Mar-20 model. On the other hand, decrements on ***ps*** are all significantly different from the normal shift, although $\boldsymbol{ps - 1Std\ Dev}$ is similar to $\boldsymbol{ps - 2Std\ Dev}$, which is similar to $\boldsymbol{-100\%\ of\ ps}$, but $\boldsymbol{ps - 1Std\ Dev}$ and $\boldsymbol{-100\%\ of\ ps}$ are different from each other. Besides, all variations (being positive or negative) in ***pc*** are significantly different from the normal shift and different from each other.

Regarding the Jul-20 model, $\boldsymbol{ps - 1Std\ Dev}$ does not imply significant difference to the normal shift. The further decrements in ***ps*** are all significant different to normal shift, despite $\boldsymbol{ps - 2Std\ Dev}$ and $\boldsymbol{-100\%\ of\ ps}$ are similar to each other. On the other hand, increments on ***ps*** are all significantly different from the normal shift and from each other. Besides, all variations (being positive or negative) in ***pc*** are significantly different from the normal shift and different from each other.

Comparing the models, from the ***ps*** perspective, for the same type of variation, the results are all similar. For instance, the scenario $\boldsymbol{ps - 1Std\ Dev}$ for Feb, Mar-20 is similar for the Jul-20 model. In the same manner, $\boldsymbol{ps + 2Std\ Dev}$ for Feb, Mar-20 is similar for the Jul-20 model, and so on. From the ***pc*** perspective, except by the scenario $\boldsymbol{pc -}$

$\mathbf{1}\boldsymbol{Std\ Dev}$**,** which is similar in both models, negative variations imply lower fatigue levels, while positive variations imply higher fatigue levels for the Jul-20 model.

Appendix E shows the p-values of the post hoc comparisons between pairs of samples using the Games-Howell method.

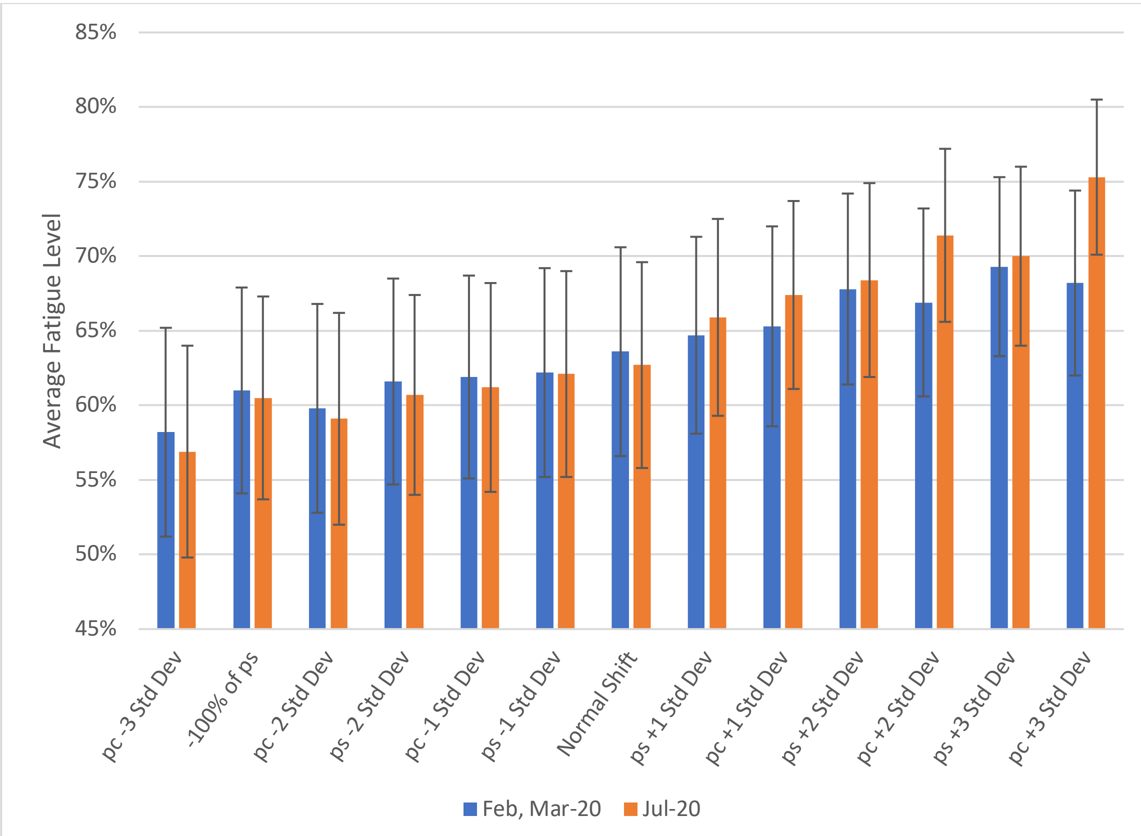


Figure 4.8. Post hoc test summary.

4.6.4 Risk of Exhaustion

In this Section, it is conducted a simulated experiment with 1,000 runs in order to verify if it is expected that a nurse reaches exhaustion during a shift scenario. In this experiment, exhaustion means 99% of maximum fatigue level during the shift. The experiment consists of testing if the average maximum fatigue level reached in a scenario is less than 0.99 (one-tailed t-test, see Table 4.20).

Table 4.20. Probability of the average maximum fatigue is less than 0.99.

Scenario	Period	Statistic	P
$pc + 3Std\ Dev$	Feb, Mar-20	-11.043	1.000
	Jul-20	6.542	**<0.001**
$pc + 2Std\ Dev$	Feb, Mar-20	-33.972	1.000
	Jul-20	-30.124	1.000
$ps + 3Std\ Dev$	Feb, Mar-20	-39.301	1.000
	Jul-20	-34.537	1.000

Figure 4.9 shows an example of fatigue behavior, comparing the scenario Feb, Mar-20 "$pc + 3Std\ Dev$" scenario, and Feb, Mar-20 normal shift.

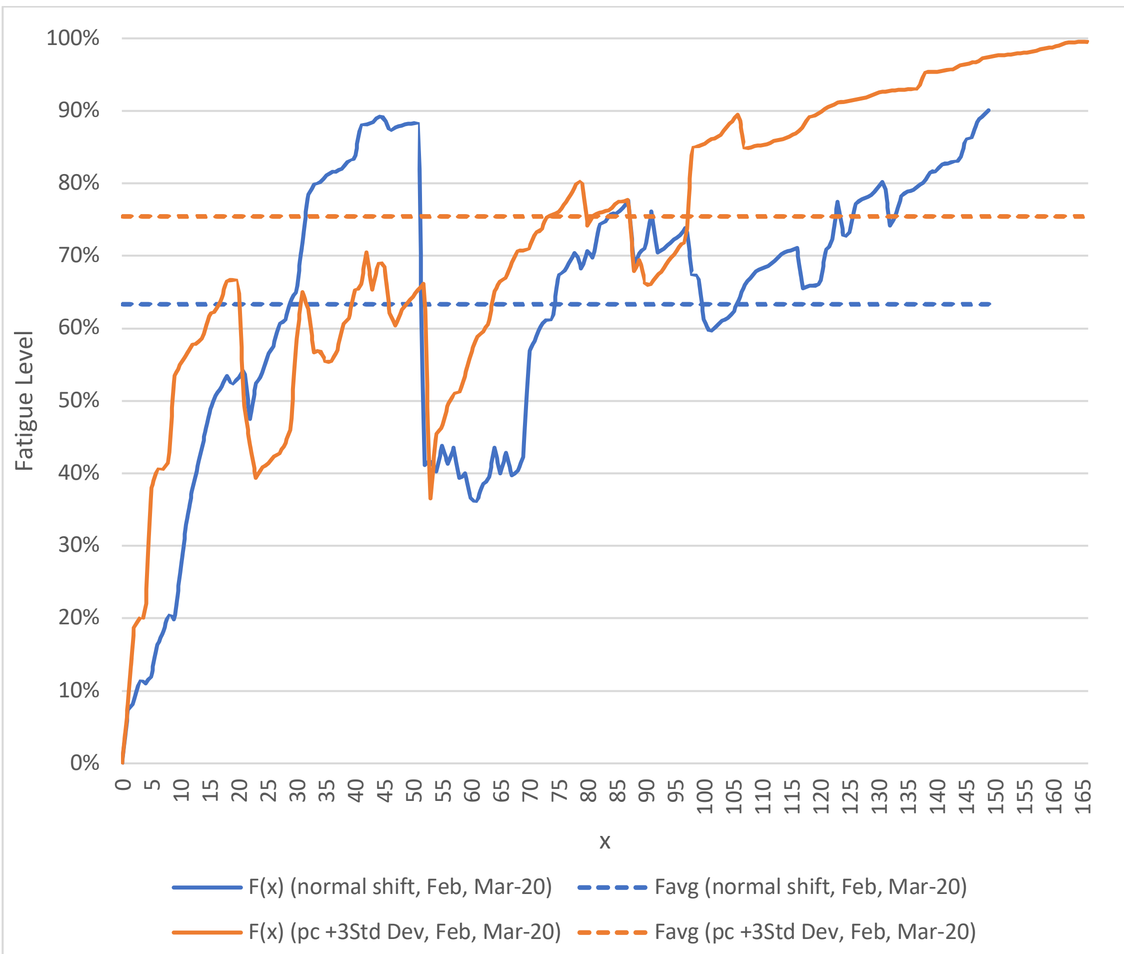


Figure 4.9. Comparing the Feb, Mar-20 normal shift and the scenario **"*pc +3Std Dev*".**

Figure 4.10 shows an example of fatigue behavior, comparing the scenario capable of leading nurses to exhaustion (see Table 4.20), the Jul-20 "$pc + 3Std\ Dev$" scenario, and Jul-20 normal shift.

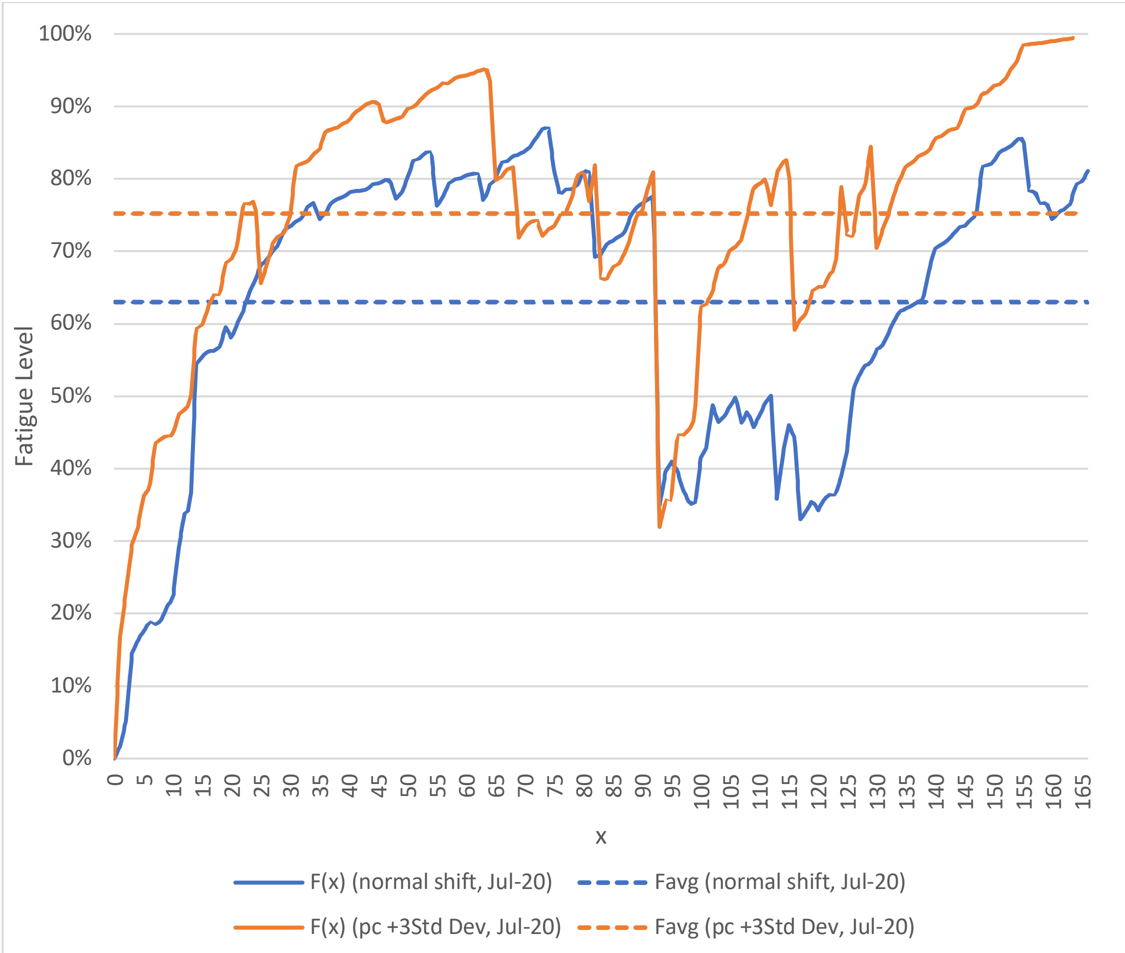


Figure 4.10. Comparing the Jul-20 normal shift and the scenario ***"pc +3Std Dev"*.**

CHAPTER 5: DISCUSSION

Besides to know the key factors responsible for nurse's fatigue during an ICU shift in each period, it is also important to understand why some of them are present in both periods or in only one and how they differ in impact magnitude in both periods.

5.1 Fatigue Due to the Total Number of Activities During a Shift

From Table 4.8, the total number of activities conducted during a shift used to be greater during the February to March 2020, and since the shifts in both periods have the same average duration of 12 hours, that suggests that nurses might have more time spent in non-valuable activities during July 2020, which explains why the average fatigue level of the data from February to March 2020 was slightly higher than July 2020 (see Table 4.3).

Besides doing more activities during February and March 2020, nurses also used to spend more time in the activities with the greatest fatigue indexes (see Appendix A, 466.48 minutes in average at in-room and out-of-room activities, and peer support put together, in comparison with 421.37 minutes during July 2020. Moreover, during July 2020, nurses used to spend about 8 minutes more in non-nursing activities (recovering activities) than during February and March 2020, that is, nurses used to have more time to recovery during July 2020. There are two possible reasons for nurses performing more tasks during February and March 2020: The first one is that it matches with the period pre-COVID-19 pandemic, while July 2020 was in the middle of the pandemic. The second one is due to the "July effect", when new interns begin learning patient care while senior residents take on additional responsibility in an academic hospital setting, creating inefficiencies in patient care, which may negatively impact quality of care (Bahl and Hixson, 2020). On the other hand, Zogg *et al.* (2022) concluded in their study no evidence of a "July effect", pointing out that the inefficiencies in patient care are due to health care systematic issues. In fact, during July 2020, nurses used to spend in average 16.5 minutes/shift teaching residents/students, while during February and March 2020, they used to send in average only 9 minutes/shift, that is, more time teaching, less time caring patients.

From the perspective of the COVID-19 pandemic impact on the nurses' workflow, recalling that the ICU in this study is a non-COVID-19 unit, other studies have shown that non-COVID units became less busy during the pandemic in some health care units around the world, such as Bodilsen *et al.* (2021), which shows that in a hospital in Demark admissions for all non-COVID-19 disease groups decreased during compared with the pre-pandemic period. Moreover, Allison *et al.* (2021) found that during the British lockdown non-COVID medical emergencies nearly halved. Allison *et al.* (2021) added that social distancing may have heralded the significant reductions in non-COVID and non-pneumonic infections in 2020 compared with 2017. Other studies also reinforce that non-COVID-19 ICUs have been less busy during the pandemic, insofar as changes in working patterns reduce risks associated with both long working hours and shift working, according to Lemiere *et al.* (2012). It is worthwhile to mention that this concentrated effort on COVID-19 units could have entailed an increment of out-of-hospital mortality due to non-COVID diseases, particularly during the lockdown weeks, as showed by Santi *et al.* (2021).

5.2 Fatigue Due to Tasks Conducted in Sequence

The number of times tasks are conducted continuously without a break (number of task sequences), both before and after lunch, are the most significant factors to nurses' fatigue during a shift in an ICU for both periods. It is worthwhile mentioning that for a 12-hour shift, the bigger the number of task sequences, the shorter the sequences and the more often breaks between them. Then, if during a shift, a nurse conducts 100 tasks using 5 task sequences, it turns out in average 20 tasks/sequence. On the other hand, for the same 100 tasks, but using 10 task sequences, it turns out 10 tasks/sequence. There is a negative correlation between the number of task sequences and the nurse average fatigue level. This study also shows that the total number of activities during a period magnifies the effect of the number of task sequences. While during the first period (February to March 2020), when the nurse used to be busier, Equation (4.1 shows that, for the variable $\boldsymbol{seq_1}$, an increment of 1 standard deviation over the mean should decrease the average fatigue level in 0.04, and for the variable $\boldsymbol{seq_0}$, an increment of 1 standard deviation over the mean should decrease the average fatigue level in 0.039, during the second period (July 2020), when nurses used to be less busy, Equation (4.2 shows that, for the variable $\boldsymbol{seq_1}$, an increment of 1 standard deviation over the mean should decrease the average fatigue level in 0.036, and for the variable $\boldsymbol{seq_0}$, an increment of 1 standard deviation over the mean should decrease the average fatigue level in 0.033.

The sequence length may explain this effect, given that during the first period (February to March 2020), in average nurse used to perform a total of 154.457 tasks in 19.327 task sequences (before and after lunch together) and during the second period (July 2020), a total of 139.8 tasks in 21.106 task sequences (before and after lunch together), it turns out an average of 7.99 tasks/sequence during the first period (February to March 2020) and of 6.62 tasks/sequence during the second period (July 2020, see Tables 4.4, 4.6, and 4.8).

5.3 Fatigue Due to Patient Care and Procedure

The variables related to tasks' frequencies are positively correlated to nurses' fatigue levels, and in periods when nurses are less busy, as during the second period (July 2020), an increase in the number of tasks impacts more the nurses' fatigue than during periods when the nurses are busier, as in the first period (February to March 2020). For example, the variable ***pc*** (number of PC3, PC4, and PC19 tasks together) is significant for both periods and have coefficient estimates of 0.01 (Equation (4.1) and 0.018 (Equation (4.2) for Feb, Mar-20 and Jul-20 models, respectively. Moreover, it makes sense that those variables are significant in both models, since those activities do not present significant differences between periods, be it in number of tasks (see Table 4.8) or in duration (see Table 4.11).

On the other hand, Table 4.12 shows that during July 2020, nurses used to perform more high-exhausting tasks, 13.66 in average, than during February and March 2020, 12.04 in average. On the other hand, medium-exhausting tasks were more frequent during February and March 2020. It is important to note that high-exhausting tasks lead nurses to complete exhaustion two times faster than the medium-exhausting ones, and this feature explains why the Jul-20 model has a greater coefficient for ***pc.*** Nonetheless, PC19 is a source of uncertainty to the model, since it is impossible to guarantee whether it refers to an PC3 (high fatigue index) or an PC4 (medium fatigue index) task, and the simulation models assume for PC19 the worst case, high fatigue index.

Moreover, that observed pattern difference, that is, procedures and contact with patients, should be strongly correlated to the need to avoid unnecessary contact with patients during the COVID-19 pandemic, in order to prevent any contaminations, as described by precautionary measures that were disseminated during the pandemic such as the article of Huang *et al.* (2020).

5.4 Fatigue Due to EMR Charting

Some variables are significant in only one model. For instance, the variable ***emr*** (number of PC9 and O11 tasks together) is significant only for the Feb, Mar-20 model. So, in a further investigation, it is possible to note that during the Feb, Mar-20 period, nurses used to conduct more EMR charting activities than during the second period, July 2020 (see Table 4.8), and those used to be longer at the same time (see Table 4.13).

5.5 Fatigue Due to Peer Support Activities

Like the variable ***pc, ps*** (peer support activities counted together) is significant for both periods and has coefficient estimates of 0.01 (Equation (4.1) and 0.018 (Equation (4.2) for Feb, Mar-20 and Jul-20 models, respectively. Moreover, it makes sense that ***ps*** is significant in both models since those activities do not present significant differences between periods (see Table 4.8).

On the other hand, Table 4.14 shows that during July 2020, nurses used to perform more high-exhausting peer support tasks, 6.64 in average, than during February and March 2020, 5.16 in average. On the other hand, medium-exhausting peer support tasks were more frequent during February and March 2020. It is important to note that high-exhausting tasks lead nurses to complete exhaustion two times faster than the medium-exhausting ones, and this feature explains why the Jul-20 model has a greater coefficient for ***ps.*** Nonetheless, PS4 is a source of uncertainty to the model, since it is impossible to guarantee whether it refers to an PS2 or PS3 (high fatigue index) or an PS1 (medium fatigue index) task, and the simulation models assume for PS4 the worst case, high fatigue index.

5.6 Fatigue Due to Talking with Patients' Families

Like the variable ***emr***, which is significant only for Feb, Mar-20 model, the variable ***twf*** (number of PC8 and O5 tasks together), the number of times the nurse talks to a patient's family is also greater during the first period (February to March 2020) compared to the second one (July 2020). This pattern suggests that during the second period (July 2020), ***twf*** frequency ranges are not enough to impact the nurses' average fatigue level. Moreover, during the pandemic, the nurses talked with the patient's family much less than before. This data suggests that during the pandemic, the access of patients' families to the hospital decreased considerably, because of organizational visiting policy changes.

5.7 Fatigue Due to Patients' Initial Assessment

Once more, one variable is significant only for the Feb, Mar-20 model, $\boldsymbol{pc_1}$, the number of initial assessments, that presented more of this type of task than for the Jul-20 model (see Table 4.8). This pattern suggests that during the second period (July 2020), those variables' frequency ranges are not enough to impact the nurses' average fatigue level. One reason for this effect may be the "July effect", when new residents start working at the hospital. During July 2020, handoffs used to be longer than in February and March 2020 (see Table 4.10) and using this time to conduct patients' initial assessment may be very useful for teaching purposes. Then, in February and March 2020, patients' initial assessments could be conducted later during the shift, and actually they used to be more frequent (see Table 4.8) and longer (see Table 4.15).

5.8 Fatigue Due to Patient's Transportation

The only observed exception was that the variable $\boldsymbol{pc_{12}}$, the number of times the nurse transported or prepared a patient to be transported, does not present significant differences in terms of frequency between periods (see Table 4.8), but it is only significant for the Jul-20 model. In a further investigation, it is possible to verify that during Jul-20, PC12 activities used to be much longer than during the first period (February to March 2020, see Table 4.9). This difference might not be related to whether the data is from the first period (February to March 2020) or second one (July 2020), but rather to the patients' clinical conditions in those specific periods, that is, the duration that a healthcare team takes to transport a patient might not be related to the period of the year the patient is in the ICU, but rather to its clinical condition.

5.9 Sensitivity Analysis

From the Tables 4.16 and 4.17, an increment in the variable ***pc*** means more procedures (PC3), patient care tasks (PC4), and closed curtain tasks (PC19), turning out less task sequences, that is, the task sequences become larger with less breaks between them. Also, the more procedures (PC3), patient care tasks (PC4), and closed curtain tasks (PC19), there will be less time to conduct other key tasks. Similarly, an increment in the variable ***ps*** means more peer support activities, turning out also less task sequences, with less time to conduct other key tasks. Recalling that an ICU nurse shift lasts in average 12 hours, then if there is a greater number of one type of tasks, there should be less of others in order to fit in the shift duration.

However, note that regardless any variation of ***pc*** or ***ps***, the variable $\boldsymbol{pc_1}$ practically does not change (see Table 4.16). From the perspective of the simulation models, $\boldsymbol{pc_1}$ happens only in phase 1 (see Section 3.3.1), that is, it is not affected by the other variables. From the perspective of a real shift, initial assessments (PC1) will be conducted regardless the nurse's other duties.

Besides, from Table 4.8, the average number of procedures and patient care activities together ***(pc)*** is about 2.2 times the number of peer support activities ***(ps).*** This fact explains why $\boldsymbol{pc}$ impacts much more the other variables than $\boldsymbol{ps}$ does. Moreover, variations in the other variables due to $\boldsymbol{pc}$ or $\boldsymbol{ps}$ magnifies the effect in the average fatigue level. For example, using Equation (4.3 alone, if $pc = 28.6$, about the value in the scenario **+23.7% of** $\boldsymbol{pc}$ in Table 4.16, the average fatigue level should have changed from 0.636 to 0.646, but that Table proves that all other key fatigue drivers are also impacted by $\boldsymbol{pc}$ variations and the simulated average fatigue level is 0.653.

While decrements in the variables related to task frequencies (those with positive coefficients) imply in a negative contribution to the average fatigue level, the variables related to task sequences ($\boldsymbol{seq_0}$ and $\boldsymbol{seq_1}$) are responsible for the opposite effect, but larger than the previous one, because those variables have the greatest absolute values in Equations (4.3 and (4.4. Moreover, the opposite is also true: A decrement of $\boldsymbol{pc}$ or $\boldsymbol{ps}$ is magnified by $\boldsymbol{seq_0}$ and $\boldsymbol{seq_1}$ as well.

It is important mentioning that the frequency distribution of the variable $\boldsymbol{ps}$ in both models is characterized by large standard deviations compared to the mean (see Tables 4.16 and 4.17). It means that the scenarios $\boldsymbol{ps - 2Std\ Dev}$ and $\boldsymbol{-100\%\ of\ ps,}$ in both models, present practically the same average fatigue outcome (see Figure 4.8).

Recalling that in Section 5.3, this study discussed about the possible reasons why the coefficient of $\boldsymbol{pc}$ is greater for the Jul-20 model (Equation (4.4) than for the Feb, Mar-20 model (4.3). This feature explains why, except by the scenario $\boldsymbol{pc - 1Std\ Dev,}$ which is similar in both models, negative variations in $\boldsymbol{pc}$ imply higher fatigue levels for the Feb, Mar-20 model, while positive variations imply higher fatigue levels for the Jul-20 model (see Figure 4.8).

Finally, for the Feb, Mar-20 model, $\boldsymbol{ps}$ will significantly impact the average fatigue level only from an increment of 2 standard deviations on, while for the Jul-20, it will impact already from 1 standard deviation on. On the other hand, $\boldsymbol{pc}$ will significantly impact the average fatigue level in both models, starting by more 1 standard deviation, but with a stronger effect on the Jul-20 model.

5.10 Risk of Exhaustion

From Table 4.20, it is possible to note that there is only scenario capable to lead nurses to a complete exhaustion, the Jul-20 **"$\boldsymbol{pc + 3Std\ Dev}$"** scenario. Despite, this scenario would happen in less than 1% of cases, it is important to identify which factors might make it feasible, in other words, how many patients assigned to a nurse might lead to this scenario.

CHAPTER 6: CONCLUSION

This study shows 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 tests 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. Also, the major drivers for nurses' fatigue in an ICU shift are the number of times nurses conduct tasks in sequence without a break (number of task sequences), followed by the number of patient care or procedures, and peer support activities conducted in shift. The latter two factors are very difficult or impossible to manage, since they depend on the number of patients assigned to the nurse, the ratio number of patients/number of nurses during a shift, and the patients' clinical conditions. Although the number of task sequences is also affected by the same mentioned factors, the tasks with a high level of predictability, such as staff huddle, clinical rounds, medication scheduling, etc., might be organized in order they do not happen close to each other. Also, it is important that nurses keep in mind that the less tasks conducted in sequence, the safer it is for them and for patients. In other words, when it is possible to choose between conducting one more task and having a break, the second option is always preferable.

One limitation in this study is that the dataset does not present the ratio number of nurses/number of patients during the shifts, and this ratio probably is strongly correlated to the peer support activities in an ICU. Another limitation is the lack of the number of patients assigned to the assessed nurses, probably strongly correlated to the patient primary care activities. Then, in future research, it is recommended to include those missing data as new independent variables to the model.

One more limitation in this study is regarding to the fatigue and recovery indexes. In this study, it is assumed three levels for the indexes, low, medium, and high, depending on the nature of the activity (see Section 3.3.5.8). It is recommended that, for the sake of more accurate results, in future studies, fatigue is monitored by a real-time method, in that way, there will be an estimated fatigue and/or recovery index for every single nurse task.

CHAPTER 7: REFERENCES

Åhsberg, E. "Perceived fatigue related to work". Ph.D. diss, University of Stockholm, Sweden, 1998.

Allison, M. C., Doyle, N. A., Greene, G., Mahmood, A., Glickman, M., Jones, A. K., Mizen, P. E. "Lockdown Britain: Evidence for reduced incidence and severity of some non-COVID acute medical illnesses". *Clin Med (Lond),* v.21(2); 2021 Mar.

Altman, M. (2002). "A review of JMP 4.03 with special attention to its numerical accuracy". *The American Statistician,* 56(1), 72-75.

Bahl, A., Hixson, C. C. (2019). "July phenomenon impacts efficiency of emergency care". *Western Journal of Emergency Medicine, 20*(1), 157.

Barnes, C. D., Laughery Jr., K. R. "Advanced Uses for Micro Saint Simulation Software". *29th Conference on Winter Simulation,* 1997.

Bodilsen, J., Nielsen, P. B., Søgaard, M., Dalager-Pedersen, M., Speiser, L. O. Z., Yndigegn, T., Nielsen, H., Larsen, T. B., Skøth, F. "Hospital admission and mortality rates for non-covid diseases in Denmark during covid-19 pandemic: nationwide population based cohort study". *BMJ,* 2021; 373: n1135.

Bradley, N. "The Response Surface Methodology". *Department of Mathematical Sciences, Indiana University of South Bend. MS in Applied Mathematics and Computer Science thesis.* 2007.

Dode, P., Greig, M., Zolfaghari, S., Neumann, W. P. "Integrating human factors into discrete event simulation: a proactive approach to simultaneously design for system performance and employees' well being". *Department of Mechanical and*

Industrial Engineering, Ryerson University, Toronto, Canada. International Journal of Production Research, Vol. 54, No. 10, 3105–3117. 2016.

Düzkaya, D. S., Kuğuoğlu, S. “Assessment of Pain During Endotracheal Suction In the Pediatric Intensive Care Unit”. *Pain Management Nursing, Vol 16, No 1 (February),* 2015: pp 11-19.

Givi, Z. S., Jaber, M. Y., Neumann, W.P. “Modelling worker reliability with learning and fatigue”. Department of Mechanical and Industrial Engineering, Ryerson University, Toronto, Canada. Elsevier, 2015.

https://humansystems.arc.nasa.gov/groups/tlx/.

Huang, L., Lin, G., Tang, L., Yu, L., Zhou, Z. “Special attention to nurses’ protection during the COVID-19 epidemic”. Critical Care (2020) 24:120.

Jaber, M. Y., Givi, Z. S., Neumann, W.P. “Incorporating human fatigue and recovery into the learning–forgetting process”. *Appl. Math. Model.* 37 (12–13) (2013) 7287–7299.

Jackson, C. (2015). The Chalder fatigue scale (CFQ 11). *Occupational medicine, 65*(1), 86-86.

Ji, Q., Lan, P., Looney, C. “A probabilistic framework for modeling and real-time monitoring human fatigue”. *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and humans*, *36*(5), (2006) 862-875.

Jones, B., Sall, J. (2011). “JMP statistical discovery software”. *Wiley Interdisciplinary Reviews: Computational Statistics,* 3(3), 188-194.

Kolodziej, K. W., Hjelm, J. “Local Positioning Systems: LBS Applications and Services”. *Boca Raton, CRC/Taylor & Francis*, 2006, p. 95.

Konz, S. “Work/rest: part II – the scientific basis (knowledge base) for the guide”, *Int. J. Ind. Ergon.* 22 (1–2) (1998) 73–99.

Kronthaler, F., Zöllner, S. (2021). “R and RStudio”. *Data Analysis with RStudio* (pp. 1-12). Springer Spektrum, Berlin, Heidelberg.

Lemiere, C., Begin D., Camus M. “Occupational risk factors associated with work-exacerbated asthma in Quebec”. Occ Health Envir Med 2012; 69:901–7.

Lim, E. J., & Son, C. G. (2022). Comparison of assessment scores for fatigue between multidimensional fatigue inventory (MFI-K) and modified chalder fatigue scale (mKCFQ). *Journal of translational medicine, 20(1),* 1-9.

Lu, L., Megahed, F. M., Sesek, R. F., & Cavuoto, L. A. (2017). A survey of the prevalence of fatigue, its precursors and individual coping mechanisms among US manufacturing workers. *Applied ergonomics, 65,* 139-151.

Min, A., Hong, H. C., & Kim, Y. M. (2021). Work schedule characteristics and occupational fatigue/recovery among rotating‐shift nurses: A cross‐sectional study. *Journal of Nursing Management.*

Miranda, D. R., Nap, RR., de Rijk, A., Schaufeli, W., Iapichino, G. “Nursing Activities Score”. *Critical Care Medicine:* February 2003 - Volume 31 - Issue 2 - p 374-382.

Moghadam, K. N., Chehrzad, M. M., Masouleh, S. R., Mardani A., Maleki, M., Akhlaghi, E., Harding, C. “Nursing workload in intensive care units and the influence of patient and nurse characteristics”. *Wiley. British Association of Critical Care Nurses.* 2020.

Montgomery, D. C. “Design and Analysis of Experiments”. 2017, 9th edition – Winley.

Oldham, K. B., Spanier, J. “An atlas of functions”. 1987, 2nd edition – Taylor & Francis/Hemisphere.

Padilha, K. G., de Sousa, R. M. C., Queijo, A. F., Mendes, A. M., & Miranda, D. R. (2008). Nursing Activities Score in the intensive care unit: analysis of the related factors. *Intensive and Critical Care Nursing, 24*(3), 197-204.

Sagherian, K., Clinton, M. E., Huijer, H. A., Geiger-Brown, J. “Fatigue, Work Schedules, and Perceived Performance in Bedside Care Nurses”. *Workplace Health & Safety, vol. 65, no.7,* July 2017.

Santi, L., Golinelli, D., Tampieri, A., Farina, G., Greco, M., Rosa, S., Beleffi, M., Biavati, B., Campinoti, F., Guerrini, S., Ferrari, R., Rucci, P., Fantini, M. P., Giostra, F. “Non-COVID-19 patients in times of pandemic: Emergency department visits, hospitalizations and cause-specific mortality in Northern Italy”. PloS One, v.16(3).

Schantz, H. G. “A Real-Time Location System Using Near-Field Electromagnetic Ranging”. *IEEE Antennas and Propagation Society International Symposium,* 2007.

Schantz H,, DePierre, R. “System and method for near-field electromagnetic ranging”. *US Patent 6,963,301,* November 8, 2005. “NFER” is a registered trademark of the Q-Track Corporation.

Schantz, H. G., Weil, C., Unden, A. H. “Characterization of Error in a Near-Field Electromagnetic Ranging (NFER) Real-Time Location System (RTLS)”. *IEEE Radio and Wireless Symposium* (2011).

Song, X., Kim, J. H. “A Time-Motion Study in an Intensive Care Unit using the Near Field Electromagnetic Ranging System”. *Industrial and Systems Engineering Conference*, 2017.

Staton, N. A. “Hierarchical Task Analysis: Developments, Applications and Extensions”. Human Factors Integration Defense Technology Centre, School of Engineering and Design, Brunel University, UK. Applied ergonomics, 2006 – Elsevier.

Vargas, V., Kim, J. H. “Learning-Forgetting-Fatigue-Recovery Simulation Model”. *Advances in Simulation and Digital Human Modeling. AHFE 2021. Lecture Notes in Networks and Systems,* vol 264. Springer, Cham.

Verzani, J. (2011). “Getting started with RStudio”. *O'Reilly Media, Inc*

Winwood, P. C., Winefield, A. H., Dawson, D., & Lushington, K. (2005). Development and validation of a scale to measure work-related fatigue and recovery: the Occupational Fatigue Exhaustion/Recovery Scale (OFER). *Journal of Occupational and Environmental Medicine,* 594-606.

Zhu, Z., Ji, Q. “Real time and non-intrusive driver fatigue monitoring”. *The 7th International IEEE Conference on Intelligent Transportation Systems (IEEE Cat. No. 04TH8749)* (2004) (pp. 657-662). IEEE.

Zogg, C. K., Metcalfe, D., Sokas, C. M., Dalton, M. K., Hirji, S. A., Davis, K. A., ... & Lichtman, J. H. (2022). “Reassessing the July Effect: 30 Years of Evidence Show No Difference in Outcomes”. *Annals of Surgery*.

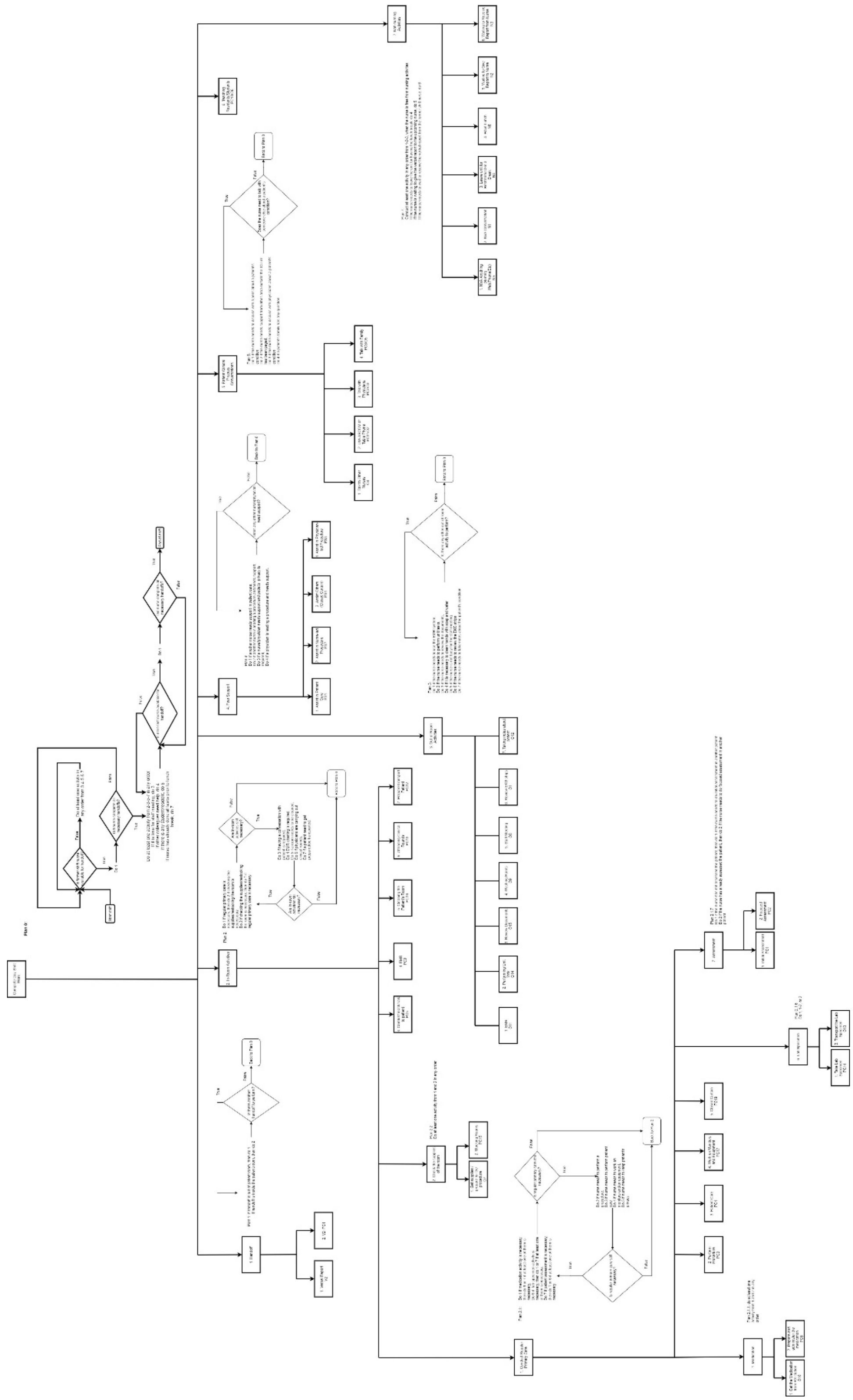
APPENDIX

Appendix A: Possible activities to be carried out by an ICU nurse

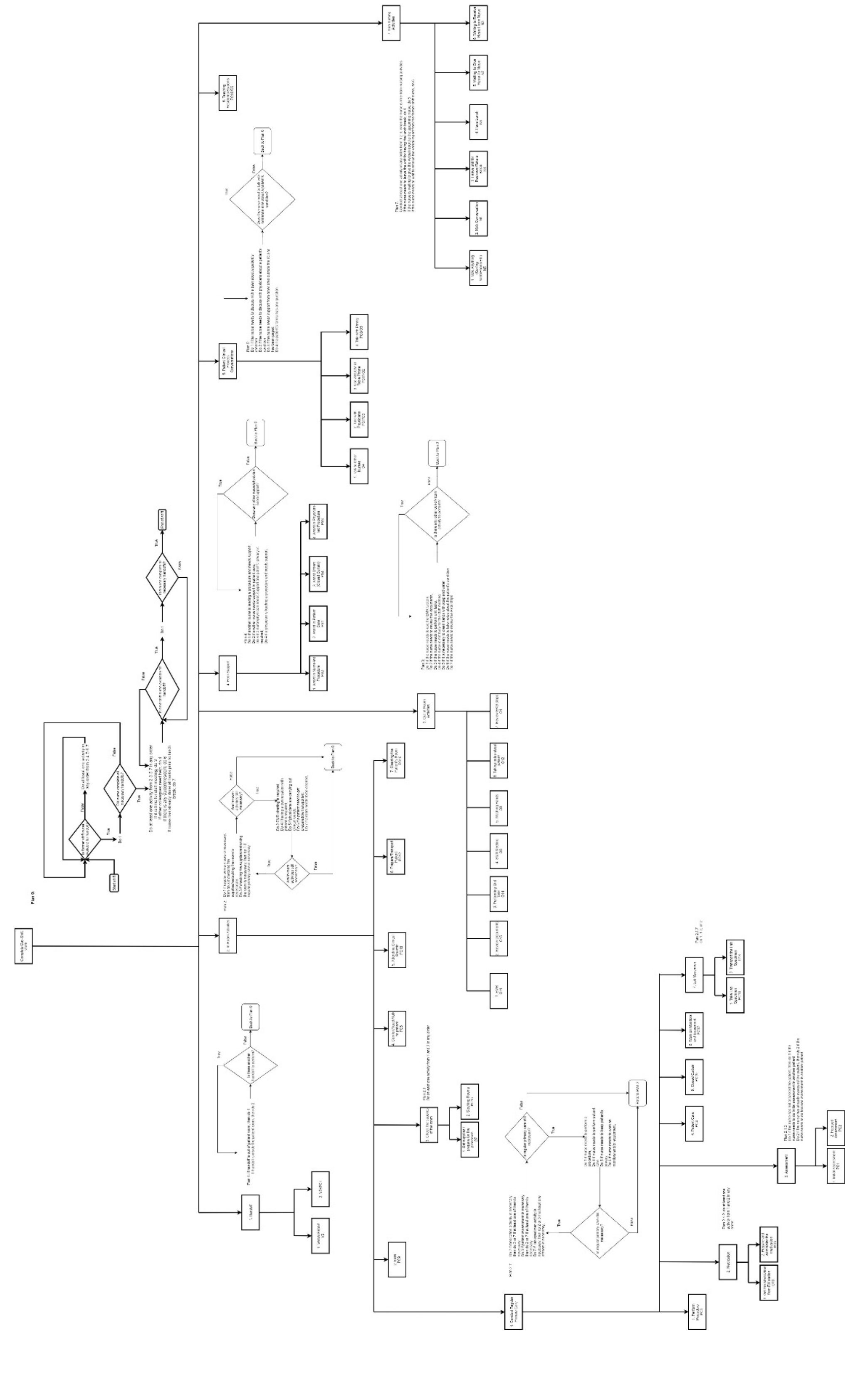
Category	Code	Description	Mental demanding	Physical demanding	Effort demanding (focus)	Time to exhaustion/recovery
Verbal Report	V2	One-to-One Meeting (Nurse Handoff)	1	0	0	12 hours
	V2+PC1	One-to-One Meeting (Nurse Handoff in Patient room)	1	0	1	8 hours
Primary Care	PC1	Initial Assessment (Vital)	1	1	1	4 hours
	PC2	Focused Assessment	1	0	1	8 hours
	PC3	Performing Procedure	1	1	1	4 hours
	PC4	Patient Care (Turning/Bathing/Etc.)	0	1	1	8 hours
	PC5	Comforting/Teaching/Talking to Patients	1	0	1	8 hours
	PC6	Preparing/Administering Medications	1	0	0	12 hours
	PC7	Talking to Physician	1	0	0	12 hours
	PC8	Talking to Family	1	0	1	8 hours
	PC9	Electronic Medical Record (EMR) Charting	1	0	1	8 hours
	PC10	Teaching Residents/Students	1	0	1	8 hours
	PC11	Using ASCOM Phone	0	0	0	null effect
	PC12	Transport Patient/Prepare for Transport	0	1	1	8 hours
	PC13	Not used in this study	-	-	-	-
	PC14	Taking Lab Specimens	1	0	0	12 hours
	PC15	Stocking Room	0	0	0	null effect
	PC16	Cleaning Room	0	1	0	12 hours
	PC17	Working on Monitors and Equipment	1	0	1	8 hours
	PC18	Attending/Participating in Clinical Rounds	1	0	1	8 hours
	PC19	Closed Curtain, Tasks Unknown	1	1	1	4 hours
Peer Support	PS1	Assisting in Patient Care (Turning/Bathing/Etc)	0	1	1	8 hours
	PS2	Assisting in Procedure (Nurse-Led)	1	1	1	4 hours
	PS3	Assisting in Physician-Led Procedure	1	1	1	4 hours
	PS4	Closed Curtain, Tasks Unknown	1	1	1	4 hours
Out-of-room Activities	O1	Printing EKG Strips	1	0	0	12 hours
	O2	Using ASCOM or Table Telephones	0	0	0	null effect
	O3	Talking with Physicians	1	0	0	12 hours
	O4	Talking with Other Healthcare Personnel	1	0	0	12 hours
	O5	Talking with Patients' Family	1	0	1	8 hours
	O6	Teaching Residents/Students	1	0	1	8 hours
	O7	Getting Supplies/Preparing for Procedures	1	0	0	12 hours
	O8	Staff Meeting (Morning Huddle)	1	0	0	12 hours
	O9	Washing Hands	0	0	0	null effect
	O10	Getting/Preparing Medications	1	0	0	12 hours
	O11	EMR Charting	1	0	1	8 hours
	O12	Taking Notes About Patients (Brains)	1	0	0	12 hours

Category	Code	Description	Mental demanding	Physical demanding	Effort demanding (focus)	Time to exhaustion/recovery
	O13	Transporting Lab Specimens	0	0	0	null effect
	O14	Performing Unit Tasks	1	0	0	12 hours
	O15	Reviewing Paper Documents	1	0	0	12 hours
Non-nursing Activities	N1	Non-Valuable Activity (NVA) Conversation	-1	-1	-1	4 hours
	N2	Waiting to Give Report to Nurse	0	-1	-1	8 hours
	N3	Waiting to Receive Report from Nurse	0	-1	-1	8 hours
	N4	Leave Unit (Restroom/Breaks)	-1	-1	-1	4 hours
	N5	NVA Anything (Surfing Web/Phone/Etc)	-1	-1	-1	4 hours
	N6	Lunch Break	-1	-1	-1	4 hours

Appendix B: Feb, Mar-20 period overall HTA chart

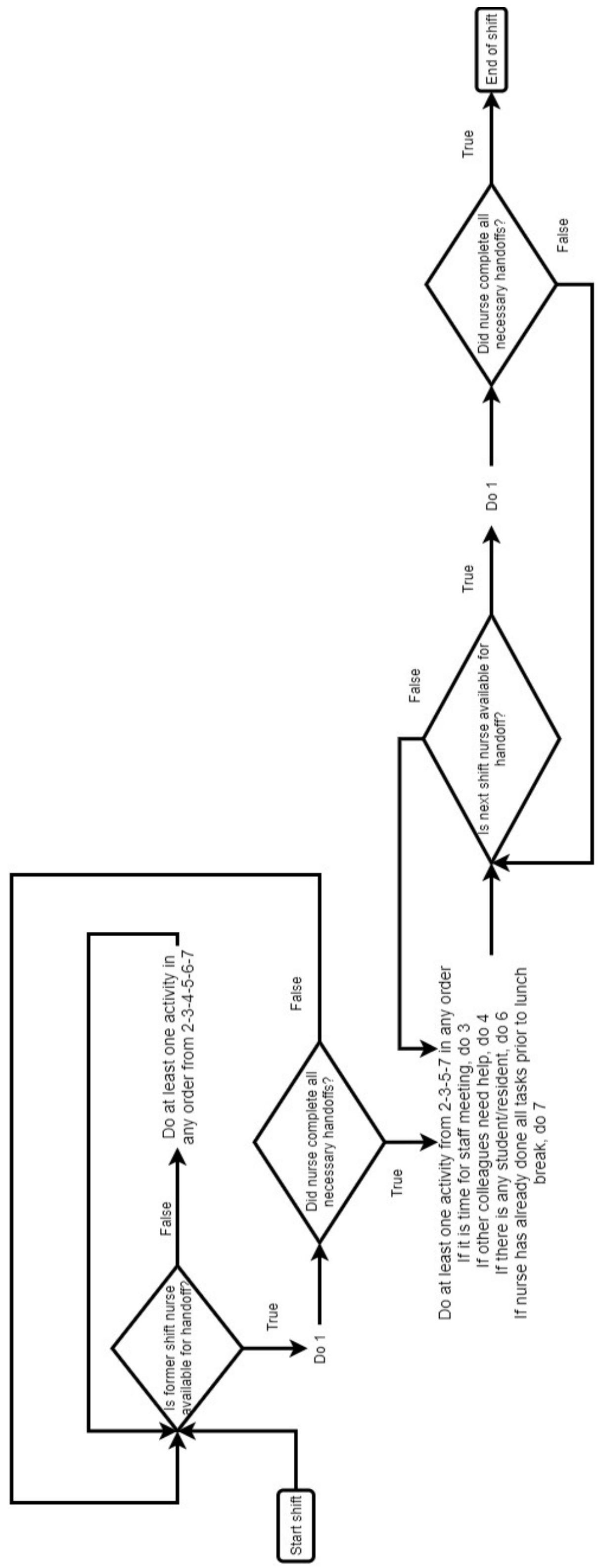


Appendix C: Jul-20 period overall HTA chart



Appendix D: Carry out the nurse workflow (Plan 0)

Plan 0:



Appendix E: P-values of the post hoc comparisons (Games-Howell)

Scenario	Feb, Mar-20 Normal Shift	-70.3% of *pc* (Feb, Mar-20)	-47.4% of *pc* (Feb, Mar-20)	-23.7% of *pc* (Feb, Mar-20)	+23.7% of *pc* (Feb, Mar-20)	+47.8% of *pc* (Feb, Mar-20)	+67.2% of *pc* (Feb, Mar-20)	-100% of *ps* (Feb, Mar-20)	-81.1% of *ps* (Feb, Mar-20)	-41.5% of *ps* (Feb, Mar-20)	+40.6% of *ps* (Feb, Mar-20)	+82.1% of *ps* (Feb, Mar-20)	+117.0% of *ps* (Feb, Mar-20)	Jul-20 Normal shift	-78.4% of *pc* (Jul-20)	-53.4% of *pc* (Jul-20)	-27.9% of *pc* (Jul-20)	+25.5% of *pc* (Jul-20)	+53.4% of *pc* (Jul-20)	+67.2% of *pc* (Jul-20)	-100% of *ps* (Jul-20)	-89.2% of *ps* (Jul-20)	-37.3% of *ps* (Jul-20)	+43.1% of *ps* (Jul-20)	+94.1% of *ps* (Jul-20)
+133.3% of *ps (Jul-20)*	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.502	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
+94.1% of *ps (Jul-20)*	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	1.000	<0.001	<0.001	<0.001	<0.001	0.951	0.187	<0.001	<0.001	<0.001	<0.001	0.196	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-
+43.1% of *ps (Jul-20)*	<0.001	<0.001	<0.001	<0.001	0.963	0.038	<0.001	<0.001	<0.001	<0.001	0.014	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-	-
-37.3% of *ps (Jul-20)*	<0.001	<0.001	<0.001	1.000	<0.001	<0.001	<0.001	0.093	0.998	1.000	<0.001	<0.001	<0.001	0.957	<0.001	<0.001	0.491	<0.001	<0.001	<0.001	<0.001	0.002	-	-	-
-89.2% of *ps (Jul-20)*	<0.001	<0.001	0.391	0.035	<0.001	<0.001	<0.001	1.000	0.633	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.997	<0.001	<0.001	<0.001	1.000	-	-	-	-
-100% of *ps (Jul-20)*	<0.001	<0.001	0.887	0.002	<0.001	<0.001	<0.001	0.998	0.195	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.003	0.857	<0.001	<0.001	<0.001	-	-	-	-	-
+67.2% of *pc (Jul-20)*	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-	-	-	-	-	-
+53.4% of *pc (Jul-20)*	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-	-	-	-	-	-	-
+25.5% of *pc (Jul-20)*	<0.001	<0.001	<0.001	<0.001	<0.001	0.990	0.466	<0.001	<0.001	<0.001	<0.001	1.000	<0.001	<0.001	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-
-27.9% of *pc (Jul-20)*	<0.001	<0.001	0.003	0.940	<0.001	<0.001	<0.001	1.000	1.000	0.231	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-	-
-53.4% of *pc (Jul-20)*	<0.001	0.380	0.914	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-	-	-
-78.4% of *pc (Jul-20)*	<0.001	0.008	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-	-	-	-
Jul-20 Normal shift	0.509	<0.001	<0.001	0.510	<0.001	<0.001	<0.001	<0.001	0.090	0.998	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-	-	-	-	-
+117.0% of *ps (Feb, Mar-20)*	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.034	<0.001	<0.001	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-	-	-	-	-	-
+82.1% of *ps (Feb, Mar-20)*	<0.001	<0.001	<0.001	<0.001	<0.001	0.373	0.998	<0.001	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-	-	-	-	-	-	-
+40.6% of *ps (Feb, Mar-20)*	0.061	<0.001	<0.001	<0.001	0.959	<0.001	<0.001	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
-41.5% of *ps (Feb, Mar-20)*	0.005	<0.001	<0.001	1.000	<0.001	<0.001	<0.001	0.028	0.967	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
-81.1% of *ps (Feb, Mar-20)*	<0.001	<0.001	<0.001	1.000	<0.001	<0.001	<0.001	0.996	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
-100% of *ps (Feb, Mar-20)*	<0.001	<0.001	0.033	0.487	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
+67.2% of *pc (Feb, Mar-20)*	<0.001	<0.001	<0.001	<0.001	<0.001	0.001	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
+47.8% of *pc (Feb, Mar-20)*	<0.001	<0.001	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
+23.7% of *pc (Feb, Mar-20)*	<0.001	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
-23.7% of *pc (Feb, Mar-20)*	<0.001	<0.001	<0.001	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
-47.4% of *pc (Feb, Mar-20)*	<0.001	<0.001	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
-70.3% of *pc (Feb, Mar-20)*	<0.001	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-