Developing an Approach to Quantify Nurse Workload and Quality of Care using Discrete Event Simulation

by

Sadeem Munawar Qureshi

Master of Quality Systems Engineering, Concordia University, 2014

Bachelor of Biomedical Engineering, NED University of Engineering & Technology, 2012

A dissertation
presented to Ryerson University
in partial fulfilment of the
requirements for the degree of
Doctor of Philosophy
in the program of
Mechanical and Industrial Engineering

Toronto, Ontario, Canada, 2020

AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this dissertation. This is a true copy of the dissertation, including any required final revisions, as accepted by my examiners.

I authorize Ryerson University to lend this dissertation to other institutions or individuals for the purpose of scholarly research.

I further authorize Ryerson University to reproduce this dissertation by photocopying or by other means, in total or in part, at the request of other institutions or individuals for the purpose of scholarly research.

I understand that my dissertation may be made electronically available to the public.

Developing an Approach to Quantify Nurse Workload and Quality of Care using Discrete Event Simulation

Doctor of Philosophy, 2020

Sadeem Munawar Qureshi

Mechanical and Industrial Engineering

Ryerson University

Abstract

Intensive workload for nurses due to high demands directly impacts the quality of care and nurses' health. To better manage workload, it is necessary to understand the drivers of workload. This multidisciplinary research provides an adaptable nurse-focused approach to discrete event simulation (DES) modelling that can quantify the effects of changing technical design and operational policies in terms of nurse workload and quality of care.

In the first phase of this research, a demonstrator model was developed that explored the impact of nurse-patient ratios. As the number of patients per nurse (nurse-patient ratio) increased, nurse workload increased, and the quality of care deteriorated. In the second phase of this research, the DES model tested the interaction of patient acuity and nurse-patient ratios. As the levels of patient acuity and number of patients per nurse increased, nurse workload increased, and quality of care deteriorated – a result that was not surprising but an ability to quantify this proactively, was conceived. In the third phase of this research, the DES model was validated by means of an external field validation study by adapting the model to a real-world unit. The DES model showed excellent consistency between modelling and real-world outcomes (Intraclass

Correlation Coefficient = 0.85 to 0.99; Spearman Rank-order Correlation Coefficient = 0.78). The fourth phase of this research used the validated simulation model to test the design implication of geographical patient bed assignment. As nurses were assigned to patient beds further away from the center of the unit or spread further apart, nurse workload increased as the nurse had to walk more leading to a deterioration in the quality of care. The DES modelling capability showed that both aspects of assignment were important for patient bed assignment. The fifth phase of this research combined Digital Human Modelling (DHM) and DES to produce a time-trace of biomechanical load and peak biomechanical load ('activity') for a full shift of nursing work. As the nurse was assigned to beds further away from the center of the unit, the cumulative biomechanical load decreased as the nurse spent more time walking yielding a reduced biomechanical load in comparison to the task group 'activity'. As patient acuity is increased, a decrease in L4/L5 moment is observed as the task duration and frequency of most care task increase. Due to increased care demands, nurses must now spend more time delivering care. Since the care demands are much higher than the current capability of nurses, quality of care is deteriorated. As number of patients per nurse, increased a 'ceiling' effect on biomechanical load can be observed as nurses do not have the time to attend to this extra demand for care. The use of this adaptable DES modeling approach can assist decision makers by providing quantifiable information on the potential impact of these decisions on nurse workload and quality of care. Thereby, assisting decision makers to create technical design and operational policies for hospital units that do not compromise patient safety and health of nurses.

Keywords:

Behavioural operations research; Discrete Event Simulation; Nurse Workload; Quality of care; Healthcare Ergonomics; Human Factors Engineering; Nurses; Healthcare policy

ACKNOWLEDGMENTS

I would like to extend my deepest gratitude to my dear supervisors *Dr. Walther Patrick Neumann* and *Dr. Nancy Purdy* for their expert guidance, support, patience and encouragement during these past few years. Not only are they true masters of their subjects but they are extraordinary human beings as well. They genuinely care for their students and are concerned about grooming them for the future. I have learned so much from them on both research and non-research realms. I will forever cherish these years that I got to train under them. I am honoured to know them and it's an absolute privilege to call them not only my mentors – but also my friends.

I am deeply grateful to my examination committee – *Dr. Michael W. Carter, Dr. Mohammad Abdoli-Eramaki, Dr. Cory Searcy* and *Dr. Filippo Arnaldo Salustri*, for taking time out of their busy schedules to be a part of the committee. Their insightful comments and enriching discussions have not only improved the quality of this research, but they have also stimulated my mind to pursue other ventures. I would also like to thank *Dr. Ahmad Ghasempoor* for his kind support.

My deepest gratitude to *Anne vanDeursen* and *Helen Kelly* - without their support, the field study would not have been possible. Thank you for letting me come to your units and letting me experience the wonderful world of nursing. I would also like to thank *Kateryna Metersky* for sharing her work experiences that enabled me to fill out gaps in the modeling logic.

This research would not have been possible without the Discovery Grant of the *Natural Sciences and Engineering Research Council of Canada (NSERC),* and the Seed Grant of the *Centre of Research Expertise for the Prevention of Musculoskeletal Disorders (CRE-MSD)*.

Special thanks to *Dr. Michael Alexander Greig* for all the laughter and long discussions on both research and non-research related areas (okay fine… mostly non-research related). I am grateful to have such a great role model. These past few years would have been indeed a struggle without you. I would also like to thank *Asad Mohani* for being my partner-in-crime at this project's inception stage.

Many thanks to the wonderful support staff, *Lynn Reynolds, Lisa Holling, Lauren Sena, Jessica Miniaci* and *Karen Fajardo*, for making the MIE department such a lovely place to work. Thank you all for your timely help. Special thanks to *Chris Chu* and *Grace He* for their constant tech support and letting me pick their brains at a moments' notice.

Lastly, I would like to thank the Almighty and my family *Lubna Imtiaz, Munawar Jamal Qureshi, Hassaan Munawar Qureshi, Maliha Hassaan (MB), Ramsha Sadeem* and *Liyana Afsar Qureshi*, for all the love, endless support, patience and sacrifices you all have made during the last few years. I am deeply grateful to have such a great support system.

DEDICATION

To my loving parents, Mamma (Lubna) and Abbu (Munawar)– anything I do, is all for you!

and

Sonu (Hassaan), thank you for forcing me to take the Human Factors course, that forever changed my life

TABLE OF CONTENTS

ABSTRACT iii

ACKNOWLEDGMENTS v

DEDICATION vii

LIST OF ABBREVIATIONS xvii

CHAPTER 1 1

INTRODUCTION 1

1.1 Background 1

1.2 Industrial Engineering (IE) Tools in Healthcare 3

1.3 Human Factors Engineering and Ergonomics in Healthcare 3

1.3.1 Lack of a Systems-based Approach 4

1.4 Conceptual Model 5

1.4.1 Healthcare System Design 7

1.4.2 Healthcare Unit System 9

1.4.3 Outcomes 12

1.5 The Need for Simulation 17

1.6 Solution Pathway: Simulation Technologies 18

1.6.1 Medical Simulators 18

1.6.2 Computerized Simulation 18

1.7 Discrete Event Simulation (DES) in Healthcare (HC) Systems 21

1.7.1 Hospital units and Clinics 21

1.7.2 Hospital flow optimization 21

1.7.3 Patient wait times 22
1.7.4 Nursing workload 22
1.7.5 Physical Layout 22
1.8 The Missing Link 23
1.9 Objective of the research 23
CHAPTER 2 26
PILOT SIMULATION MODEL 26
2.1 Methods 26
2.2 Model Inputs 27
2.2.1 Patient care data 27
2.2.2 Operating Logic 28
2.2.3 Virtual layout of the Discrete Event Simulation (DES) model 31
2.3 Outputs 31
2.4 Demonstrator Model Testing 32
2.5 Results 32
2.5.1 Nurse Workload Indicators 33
2.5.2 Quality of Care Indicators 33
2.6 Discussion 34
2.7 Implications to Nursing Management 35
2.8 Methodological Issues for the Demonstrator Model 36
2.9 Conclusion 37
CHAPTER 3 38
PILOT MODEL EXTENSION: NURSE-PATIENT RATIO & PATIENT ACUITY 38
3.1 Methods 38
3.2 Model Inputs 39

3.2.1 Patient care data 39

3.2.2 Operating Logic 40

3.2.3 Virtual layout 42

3.3 Model Outputs 42

3.4 Experimental Design and Analysis 43

3.5 Modelling experiment 43

3.6 Model Verification 44

3.7 Results 44

3.7.1 Quality of care indicators 45

3.7.2 Nurse workload indicators 46

3.8 Model Verification 50

3.9 Discussion 51

3.10 Methodological Modelling Issues for the Demonstrator Model 53

3.11 Implications for Healthcare System Engineering 55

3.12 Conclusion 55

CHAPTER 4 57

MODEL VALIDATION 57

4.1 Validating computerized simulation models 57

4.2 Methods 58

4.2.1 Model Creation 58

4.2.2 Internal Validation of the Model 62

4.2.3 External Model Validation using Field Data 63

4.2.4 Modelling Conditions 65

4.3 Results 66

4.3.1 Modeling Results 66

4.3.2 Internal Validation of the Model 67
4.3.3 External Validation of the model – Field Study 67
4.4 Discussion 71
4.4.1 Adapting the DES Model to Medical-surgical Unit 71
4.4.2 External Validation from Field Study 72
4.4.3 On the Issue of Model Validation 75
4.4.4 Model Implications and Applications 76
4.5 Conclusion 77
4.6 Ethics approval 78
CHAPTER 5 79
GEOGRAPHICAL PATIENT-BED ASSIGNMENT 79
5.1 Methods 79
5.2 Model Inputs 80
5.2.1 Hospital Unit Floorplan 80
5.2.2 Patient Care Data 81
5.2.3 Nurse Operating Logic 82
5.2.4 Nurse walking patterns 83
5.2.5 Modelling Outputs 84
5.2.6 Average Inter-Bed distance (IBD) and Average Bed-Nurse Station distance (BND) . 84
5.2.7 DES Model Testing 86
5.2.8 Model Verification 87
5.3 Results 87
5.3.1 Nurse Workload Indicators 87
5.3.2 Quality of Care indicators 88
5.4 Discussion 90

5.4.1 Inter-Bed distance vs. Bed-Nurse Station distance 90
5.4.2 Nurse Workload Indicators 92
5.4.3 Quality of Care Indicators 93
5.4.4 Methodological Modelling Issues 93
5.4.5 Implications to Healthcare Systems Engineering 94
5.5 Conclusion 95
CHAPTER 6 96
BIOMECHANICAL LOAD MODELING 96
6.0 Methods 96
6.1 Model Creation 96
6.1.1 Model Inputs 97
6.1.2 Model Outputs 100
6.2 Demonstrator Case 100
6.3 Results 102
6.3.1 Experiment 1: Geographical-based Patient-Bed Assignment Results 103
6.3.2 Experiment 2: Patient Acuity results 105
6.3.3 Experiment 3: Nurse-patient ratio results 105
6.4 Discussion 107
6.4.1 General simulation results 108
6.4.2 Experiment 1: Geographical patient-bed assignment results 109
6.4.3 Experiment 2: Patient acuity results 110
6.4.4 Experiment 3: Nurse-patient ratio results 110
6.4.5 Implications for the Healthcare industry 110
6.4.6 Methodological Modelling Limitations 111
6.5 Conclusion 112

6.6 Ethics approval 113

CHAPTER 7 114

DISCUSSION 114

7.1 General Overview 114

7.2 RQ 1 – Pilot DES Model Creation and Demonstrator Case 115

7.3 RQ 2 – Pilot DES Model Extension: Patient Acuity and Nurse-Patient Ratio 115

7.4 RQ 3 – Model Validation via Field Study 117

7.5 RQ 4 – Geographical-Patient Bed Assignment 118

7.6 RQ 5 – Biomechanical Loading and MSD risk of Nurses 118

7.7 RQ6 – Biomechanical loading and MSD risk under different technical designs 119

7.8 Contributions 120

7.9 Methodological Discussion 123

7.10 Future work 125

7.10.1 Extending the DES modeling capabilities 125

7.10.2 Potential Issues 126

7.10.3 Potential Users 128

CHAPTER 8 131

CONCLUSION 131

REFERENCES 135

LIST OF FIGURES

Figure 1 illustrates the Conceptual Model of this PhD Thesis 6
Figure 2 illustrates the Inputs and Outputs of Pilot DES model 27
Figure 3 illustrates the flow chart representing the operating logic of the DES model 30
Figure 4 represents the Nurse Workload indicators: Mean and St. Deviation of 'No. of Task Queue' (left) and 'Distance walked by Nurse' (right) 33
Figure 5 represents the Quality of Care indicators: Mean and St. Deviation of 'Missed care' (left) and 'Task in Queue time' (right) 34
Figure 6 represents the Inputs and Outputs of the extended Pilot DES model 39
Figure 7 illustrate the average number of Missed care (tasks/shift) per shift 45
Figure 8 represents Missed care delivery time (hours/shift) per shift 46
Figure 9 illustrates Care delivery time (hour/shift) 47
Figure 10 show the average number of Task in queue (tasks/shift) per shift 47
Figure 11 illustrates how the inputs (healthcare system design and policies) and outputs (nurse workload and quality of care) of the DES model are validated by a series of validity checks 60
Figure 12 illustrates the 'Distance walked by Simulated-Nurse' and 'Distance walked by Nurse' (measured using Fitbit™) 68
Figure 13 represents the movement of simulant-nurse, following task priority rank sequence and actual nurse 69
Figure 14 represents an overview of the DES model used for testing Geographical patient-bed assignment 80
Figure 15 shows the floorplan from the Selected Medical-surgical Unit (not to scale) 81
Figure 16 illustrates the block diagram showing how DHM and DES modeling capabilities are combined 97
Figure 17 represents the time-trace graph for the L4/L5 moment for the baseline case 102
Figure 18 illustrates the percentage difference from the baseline case of 'cumulative L4/L5 compression load' and 'distance walked' 104

Figure 19 illustrates the percentage difference from the baseline case of 'cumulative L4/L5 moment' and 'distance walked' 106
Figure 20 represents a saturation effect for the biomechanical load 'cumulative L4/L5 compression load' and 'cumulative L4/L5 moment' 107
Figure 21 illustrates how a design orientated approach can address the needs of the healthcare professionals (HCP) and patients, by focusing on the health and workload of HCP(in this case, nurses), and the quality of care delivered to patients. 116
Figure 22 illustrates the scope of this multidisciplinary research conducted in this PhD thesis (Industrial Engineering; Healthcare, e.g. Nursing; Human Factors) 120

LIST OF TABLES

Table 1: List of tasks programmed in the DES model. 29
Table 2 illustrates the results for Quality of Care and Nurse workload indicators 32
Table 3 illustrate the patient care delivery tasks, programmed in the DES model 41
Table 4 show the effect of varying Patient acuity levels & Nurse-patient ratios in terms of 'Quality of care' & 'Nurse workload' indicators 49
Table 5 illustrates the task priority rank generated from both focus groups. 61
Table 6 provides a summary of the modelling outcomes as reported by the DES model 66
Table 7 illustrates the Rank order and Percentage divisions for Missed care for Simulant-nurse and Actual nurse (Perceptions of Missed Care – MISSCARE Survey) 68
Table 8 illustrates the percentage division of Missed care tasks for the Simulant-nurse (following task priority rank 1 and 2), and Nurse's perception from the MISSCARE Survey 70
Table 9 illustrate the DES Model Care Task Groups, Priority level (1 = Highest; 6 = Lowest), Scheduling Type and Time Duration (Frequency weighted). 82
Table 10 - An example of the walking pattern for nurses while performing care tasks 84
Table 11 – Experimental conditions in this study, where, * represents typical patient bed assignments of an experienced nurse 86
Table 12 provides a summary of the Impact of Geographical Bed Assignment on Nurse Workload and Quality of Care Indicators 89
Table 13 illustrates the care task programmed in this study along with 'Care task scheduling type', 'Time duration' and 'Care task priority rank' 99
Table 14 illustrates the experimental designs for this study 101
Table 15 illustrates the Peak L4/L5 moment and compression load for the care tasks programmed in the simulation model 103
Table 16 illustrate the results for Experiment 1: Geographical-based Patient-bed assignment 104
Table 17 illustrate the results for Experiment 2: Patient acuity 105
Table 18 illustrate the results for Experiment 3: Nurse patient ratio 106

LIST OF ABBREVIATIONS

ABM	Agent-Based Modelling
ANOVA	Analysis of Variance
BND	Bed-Nurse Station Distance
CAPCR	Coordinated Approval Process for Clinical Research
CNFU	Canadian Federation of Nurses Unions
CQ	Care Quality
DES	Discrete Event Simulation
DHM	Digital Human Model
GIGO	Garbage-in Garbage-out
GRASP	Grace Reynolds Application of the Study of PETO
HCP	Healthcare Professional
HF	Human Factors
HR	Human Resources
IBD	Inter-Bed Distance
ICC	Intraclass Correlation Coefficient
IE	Industrial Engineering
IEA	International Ergonomics Association
IISE	Institute of Industrial and Systems Engineers
MSD	Musculoskeletal Disorders

NIOSH	National Institute for Occupational Safety and Health
NPR	Nurse-patient ratio
ONA	Ontario Nurses Association
PA	Patient Acuity
PETO	Poland, England, Thornton, and Owens
REB	Research Ethics Board
REBA	Rapid Entire Body Assessment
RN	Registered Nurse
RPN	Registered Practical Nurse
RQ	Research Question
RULA	Rapid Upper Limb Assessment
SBR	Simulated-based research
SD	System Dynamics
SEIPS	Systems Engineering Initiative for Patient Safety
SME	Subject Matter Expert
WE	Work Environment
WHO	World Health Organization
WL	Workload

CHAPTER 1

INTRODUCTION

The background and the underlying reason for conducting this research are provided in this chapter. A discussion of the current challenges faced in healthcare is followed by current limitations of industrial engineering (IE) tools used in this setting. Next is a description of the conceptual model followed by a description of how simulation can be used to proactively quantify nurse and patient outcomes. The chapter ends with the presentation of research objectives for the series of studies that were conducted.

1.1 Background

A poor work environment not only costs the Canadian healthcare system (HCS) excessive capital each year but also has negative consequences on healthcare professional's well-being. In 2014, The Canadian healthcare sector was reported to have the highest number of lost time injuries including work-related musculoskeletal disorders, workplace violence, exposures and falls; making nursing the highest risk job compared to manufacturing and mining industries (Canadian Federation of Nurses Unions, 2015). In same year, 21,000 Registered Nurses (RN) were absent each week due to an illness/disability which led to a $846.1 million in replacement cost (Silas, 2015). In the United States, the replacement cost for hiring a nurse was estimated to be up to $105,000 USD per nurse (Occupational Safety and Health Administration, 2013). The total annual cost of absenteeism for Canadian Nurses in 2010 was $711 million (Gormanns, Lasota, McCracken, & Zitikyte, 2011). Furthermore, the combination of absenteeism and under-staffing contributes to an increased workload for caregivers already struggling to keep up with their current work demands. In 2014, 19,383,900 overtime hours were reported for nurses in Canada. This is equivalent to 10,700 full time positions and carries an estimated cost of $871.8 million dollars (Canadian Federation of Nurses Unions, 2015). Canadian public sector nurses worked

20,627,800 hours of overtime in 2010, the equivalent of 11,400 jobs costing $891 million/year (Gormanns et al., 2011). The work environment is an emergent characteristic of the healthcare system design and the product of many different decisions. Determining how policy and design decisions will affect staff is challenging and the costs of a poor work environment are not well understood.

In a national study of nurses' health, 37% of nurses had experienced pain that was attributed to work-related factors 75% of the time and was serious enough to prevent them from carrying out their normal daily activities (Statistics Canada, 2006). The Registered Nurses Association of Ontario, (2008) reported that unhealthy work environments contributed to the current nurse shortage. Nurse turnover is highly influenced by the quality of the work environment; a higher workload affects nursing turnover rates, and disrupts the quality of care and patient safety (McGillis Hall et al., 2005). Poor work environments can lead to overworked nurses and fatigue. This in turn can cause nurses to have less alertness to changes in patients' conditions, slower reaction times, and an increased rate of medication errors, all of which translate into adverse risks to patients (International Council of Nurses, 2015). Research on fatigue shows that the decrement of worker performance effects are on par with alcohol intoxication (Dawson & Reid, 1997). Improving nurses' work environments can reduce fatigue and associated adverse outcomes, such as mistakes, lapses and slip type errors that are the consequence of the design of the healthcare system (Reason, 2004). Reducing fatigue can thus improve delivery of care to the patient—and also address the need to retain sufficient qualified nurses (Australia Nursing Federation, 2009). A positive work environment improves the productivity of healthcare workers and results in a higher employee retention rate, which leads to a larger pool of highly competent caregivers, better teamwork, increased continuity of patient care, and ultimately improvements in patient outcomes (Registered Nurses Association of Ontario, 2008). Positive work environments are work settings that not only support the personal well-being of healthcare workers but also help to maintain good patient care standards. Nurses who have experienced improved work environments and reduced workloads have reported an increased quality of care and patient satisfaction (Aiken et al., 2012; Carayon et al., 2011; Purdy, Laschinger, Finegan, Kerr, & Olivera, 2010). The ability to quantify the effects of healthcare system design decisions on the quality of the work environment and their subsequent impact on nurse workload remains a challenge.

1.2 Industrial Engineering (IE) Tools in Healthcare

To improve healthcare processes and the subsequent impact on workload, several healthcare organizations have implemented industrial engineering (IE) process improvement techniques to enhance the quality of care, efficiency and patient safety, but changes have often been at the expense of healthcare professional (HCP). Popular IE techniques such as Lean interventions, have been implemented but there is evidence of long-term negative effects on HCP workload (Drotz & Poksinska, 2014; Parker, 2003). Along with an increased potential for making mistakes, injuries, work-related musculoskeletal disorders (MSD) and missing less urgent care tasks have led to a reduction in the quality of care (Moraros, Lemstra, & Nwankwo, 2016; Westgaard & Winkel, 2011). Other process improvement strategies to increase efficiency are sometimes accompanied by negative effects such as the degradation of the HCP's health, satisfaction and engagement, workload issues, availability of supplies, increased stress and reduced safety for patients (Carayon, Wetterneck, et al., 2014). Engineering tools applied in healthcare processes have shortcomings when they do not consider the impact on the HCP. HCPs are critical to the healthcare system and the quality of care delivered to patients. Without considering HCPs, the healthcare system ultimately fails, regardless of how sophisticated the technology is (Neumann et al., 2018). However, human factors (HF) engineering and ergonomic principles may help as these techniques are user-centered as they take into consideration the worker, in this case the HCP (Dode, Greig, Zolfaghari, & Neumann, 2016; Holden et al., 2013; Village, Greig, Salustri, & Neumann, 2012). This thesis makes use of HF engineering and ergonomic principles and methodologies to examine nurse workload and quality of care.

1.3 Human Factors Engineering and Ergonomics in Healthcare

The International Ergonomics Association [IEA] (2018) defines ergonomics (or human factors) as: 'the scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data and methods to design in order to optimize human well-being and overall system performance'. The application of human factors (HF) concepts, methodologies and tools to improve patient safety have been advocated by several professionals (Carayon, 2010; Holden et al., 2013; Reid, Compton, Grossman, & Fanjiang, 2005). The earliest implementation of HF in the field of healthcare can be traced back to the early 1960s. The critical incident technique was used to examine medication errors in hospitals over a period of seven months (Chapanis & Safrin, 1960). These errors were classified into seven different categories: wrong medication dosage, wrong patient, medication not administered etc. Even though this research led to some useful recommendations for preventing medication errors, human factors were still not considered critical for patient safety (Carayon, Wetterneck, et al., 2014). However, after the release of the report: "To Err is Human: Building a Safer Health System" by Kohn et al. (1999), the World Health Organization (WHO) curriculum on patient safety now included the importance of HF in patient safety and patient care (Walton et al., 2010).

Ignoring HF means a lack of focus on the user which can lead to a direct impact on efficiency, productivity, resistance to newer technical design and operational policies, injury, burnout and increased costs, decreased quality and the ability to implement newer technologies (Chuang, Tseng, Lin, Lin, & Chen, 2016; Kalisch & Williams, 2009; Yoder, 2010). A lack of application of HF when establishing a new system impacts the health of the worker (Neumann, Winkel, Medbo, Magneberg, & Mathiassen, 2006; Neumann, Kihlberg, Medbo, Mathiassen, & Winkel, 2002). By using HF, these effects can be mitigated while service quality can be improved (Neumann & Dul, 2010). Some HF tools include Rapid Upper Limb Assessment (RULA) (McAtamney & Corlett, 1993), Rapid Entire Body Assessment (REBA), (Hignett & McAtamney, 2000), Borg's Scale (Borg, 1990, 1998), 4DWATBAK (Neumann, Wells, & Norman, 1999), WEE tool (Greig, Village, Salustri, Zolfaghari, & Neumann, 2018; Greig, 2016) etc. These tools have been successful in manufacturing, but there is no known tool that can integrate HF into the healthcare process improvement. Current approaches such as the trial and error method can be very expensive and hazardous (Gaba, 1999, 2007), as that would lead to exposing workers to unsafe and untested environments that can not only effect their health but also decrease productivity and the process efficiency, and deteriorate the quality. In this thesis, a tool is developed that integrates HF into the process improvement of healthcare.

1.3.1 Lack of a Systems-based Approach

In the past, some consideration has been given to users at the design stage, but these have had limited success as they do not take into consideration the needs and performance of other departments. An example is changing the physical design of a patient monitor that makes a beeping noise with each heartbeat which can be annoying for some patients as they wish to sleep. If researchers develop a new model that does not make any beeping noise then it will work well for that specific unit but not for other units such as the Intensive Care Unit and Coronary Care Unit (CCU), as patients admitted there have a higher acuity level and the beeping sounds allows the HCP to know if the patient is deteriorating. Therefore, a system should be treated as a whole, instead of addressing separate goals. Given the complex interconnected design of delivering care, the lack of a systems approach may result in a lowered quality of care, patient safety and productivity (Carayon et al., 2006; Carayon, Wetterneck, et al., 2014). In this thesis, a tool was developed that helps examine and quantify the impact of process of care delivery under different technical designs and operational polices at the systems level as further explained in the next section.

1.4 Conceptual Model

The conceptual model used for the proposed set of studies is a systems-based approach where the system should be treated as a whole, instead of addressing separate goals. This conceptual model builds on the SEIPS 2.0 (Systems Engineering Initiative for Patient Safety) model by Holden et. al. (2013), that provides a framework for understanding the role of HF in healthcare systems. SEIPS 2.0 is an extension to the first model proposed by Carayon et.al., (2006) which is a macro-ergonomic work systems model for patient safety and the work environment system that focuses on the organization-system interaction. SEIPS 2.0 is a conceptual model and analytic tool that describes how sociotechnical systems can transform healthcare work done by both, healthcare-professionals and non-healthcare professionals – collaboratively and independently. SEIPS 2.0 follows the 'Structure' (Design), 'Process' (Healthcare unit system) and 'Outcome' (HCP, patient and organizational outcomes) format of the 'Quality of Medical Care' model developed by Donabedian (1978).

As illustrated in Figure 1, a more design-oriented approach to the SEIPS 2.0 model was proposed to support efforts in improving performance in existing healthcare units. This design-oriented approach provides insight into how the healthcare system design can impact the healthcare system process and its outcomes. In addition, this design oriented SEIPS model addresses the needs of both the HCPs and patients in the improvement process. Examples of healthcare system design decisions are staffing strategies, physical layout, geographical-patient bed assignment, patient acuity and care procedures. The healthcare system unit includes: HCP, process of care

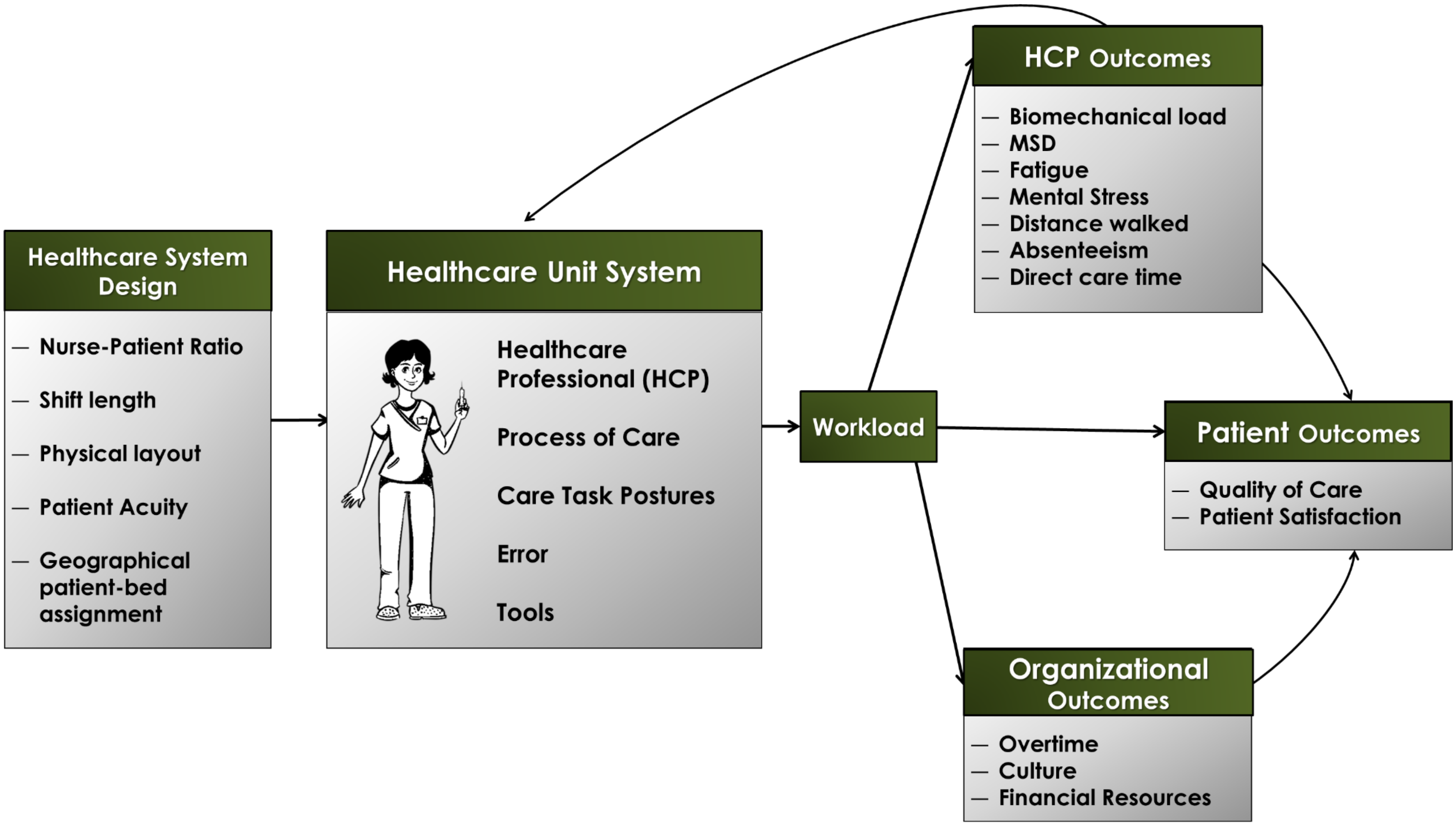

Figure 1 illustrates the Conceptual Model of this PhD Thesis. The Conceptual Model comprises of Design parameters, Healthcare unit system, Workload and Outcomes (HCP, Patient and Organizational) delivery and work environment. Workload is one component of healthcare unit system. Workload directly impacts the HCP, the patient and the organization (Weigl, et al., 2014). HCP outcomes include biomechanical load, work-related MSD, fatigue, mental stress, distance walked, absenteeism and direct care time. Patient outcomes entail the quality of care received and patient satisfaction. Organizational outcomes examples are overtime, culture and financial resources. Patient and organizational outcomes both effect HCP outcomes that impacts the healthcare system unit. A subset of these variables will be simulated using discrete event simulation (DES). Simulation will be discussed in detail in Section 1.5 (p.17). The focus of this thesis is an exploration of both HCP and patient outcomes.

1.4.1 Healthcare System Design

In the 'design' process of the healthcare system, decisions are made about technical design and operational polices. Some examples of the design parameters are nurse-patient ratios, shift length, physical layout of the facility (hospital), patient acuity and geographical patient-bed assignment. These are described below.

Nurse-patient ratio (NPR) represent the number of patients assigned to one nurse in one shift (Qureshi, Purdy, & Neumann, 2016). The greater the number of patients assigned to one nurse, the greater the nursing workload (Park, Weaver, Mejia-Johnson, Vukas, & Zimmerman, 2015). High nurse-patient ratios increase the risk of making an error thereby compromising patient safety (Rogers, Hwang, Scott, Aiken, & Dinges, 2004). Staffing ratios are central to the provision of quality of care in healthcare systems (Brennan, Daly, & Jones, 2013; McGillis Hall et al., 2005). The reduction in staff is done mostly on the basis of cost efficiency which leads to understaffing (Letiche, 2008). Adverse effects arising from understaffing can lead to overtime and excessive workload giving rise to stress, fatigue, work-related MSD, absenteeism and eventually burnout or injury (Brennan et al., 2013; Davey, Cummings, Newburn-Cook, & Lo, 2009; Oliva & Sterman, 2001; Registered Nurses Association of Ontario, 2008). The impact of changing nurse-patient ratios on HCP and patient outcomes is examined in this thesis.

Shift length entails the total time a nurse must work in one shift per day. Increased shift length has been linked to increased fatigue, burnout, errors, MSD risk and injuries (Stimpfel, Sloane, & Aiken, 2012). Shift length for nurses varies in different countries. In most cases, the shift length is

8, 10 or 12 hours (Garrett, 2008). This thesis made use of the Canadian healthcare standard in acute care by exploring 12 hours shifts.

The **physical layout** is the floorplan of a hospital or unit. The layout is comprised of patient bedrooms, washrooms, nurse station, clean and dirty utility rooms. The floor plan also contains the size and dimensions of patient rooms, utility rooms, nurses' station, corridors, washroom, and their alignment (Choudhary, Bafna, Heo, Hendrich, & Chow, 2010). Physical layouts are used to assess performance estimates for HCPs as the layout of the unit directly contributes to the walking time and walking distance of HCPs (Boucherie, Hans, & Hartmann, 2012; Brennan et al., 2013). Increased walking distances have been associated with fatigue, overtime and burnout (Hendrich, Chow, Skierczynski, & Lu, 2008). Increased walking distances are affected by the geographical patient-bed assignment, where nurses are assigned to patients in rooms at varying distances from one another. The physical layout of neurological and medical-surgical units were tested in this thesis.

Geographical patient bed assignment is the location of patients and their beds assigned to a nurse for the duration of a shift. Determining the patient-bed assignments for each nurse is a difficult process (Cignarale, 2013). The charge nurse who assigns nurses to all patients in the unit considers the patient acuity level, the amount of care to be delivered to each patient and the location of patient bed (Acar & Butt, 2016). Given the increased demand for healthcare services, hospitals are forced to operate at a full or nearly full patient bed occupancy, and the geographical location of each patient the nurse is assigned to is often overlooked. As a result, it is very common for a nurse to have patients assigned that are not close to each other and it is no surprise that nurses spend a large proportion of their time walking during their shifts which adds to their workload (Hendrich et al., 2008; Hua, Becker, Wurmser, Bliss-Holtz, & Hedges, 2012; Yi & Seo, 2012). Nurse walking distance is contingent upon unit layout i.e. room size, floor plan, and patient bed assignment (how far/close all patient rooms are to each other, for one nurse). Acar & Butt (2016) studied the travel distance as a weighted function of the distance between two patient rooms, distance between the patient room and supply room, and distance between the patient room and nurse -station. Sundaramoorthi et al., (2009) used a tree-based model and kernel density function to study patient assignments. While patient-bed assignment has been studied to address workload issues and cost (Guido, Groccia, & Conforti, 2018; Mullinax & Lawley, 2002; Rosenberger, Green, Keeling, Turpin, & Zhang, 2004), there is a lack of focus on the development of a tool that can proactively quantify the impact of changing geographical bed assignments on nurse workload and quality of care. This gap is addressed in this thesis where the impacts of geographical patient bed assignment are quantified.

Patient acuity is defined as the level of illness of the patient. Patients bearing different acuity levels tend to require different intensities of care, depending on patient health status and treatment protocols (Liang & Turkcan, 2016). Given the increased demands, newer healthcare policies have been implemented to improve system throughput by discharging patients earlier (Qureshi, Purdy, & Neumann, 2019). This leads to increased average acuity levels of the remaining patients contributing to a higher workload among nurses. These high workload demands fall directly on an already overworked nursing population (Aiken, Clarke, Sloane, Sochalski, & Silber, 2001; Aiken et al., 2018; Daly & Brennan, 2009; Hurst, 2018). The negative effects arising from increased workload are overtime, decreased morale, dissatisfaction and absenteeism. A combination of these effects along with other organizational factors leads to burnout or WMSD (Hughes, 2008). The Registered Nurse (RN) population in United States has decreased by 13% over the course of 5 years from 2008 to 2012 (Acar & Butt, 2016). Nurses who provide care for patients with higher levels of acuity report increased levels of fatigue as compared to other nurses (Barker & Nussbaum, 2011), which gives rise to deteriorated job performance, increased medical errors and compromised patient safety (Malhotra, Jordan, Shortliffe, & Patel, 2007; Rhéaume & Mullen, 2018). The impacts of patient acuity levels were studied and quantified using a simulation tool developed for this thesis.

1.4.2 Healthcare Unit System

As illustrated in Figure 1, the components of the healthcare unit system for the proposed studies are*: healthcare professional, the process of care, tasks, tools, organization, workload* and *work environment.* These are described below.

Healthcare professionals (HCP) possess discipline-specific knowledge used for patient care delivery. HCP span a wide variety of personnel such as registered nurses (RN), registered practical nurses (RPN), physiotherapists, physicians, surgeons etc. Since 75% of the care delivered in hospital settings are by nurses (Nursing Task Force, 1999), this thesis simulated the healthcare unit system from the perspective of nurses. This new perspective offers a novel insight as most studies have been limited to physicians and doctors (Qureshi, Purdy, Mohani, & Neumann, 2019)

The **process of care** consists of cognitive, social/behavioural and physical performance components of care processes. For instance, the process to administer medication that encompasses several steps and involves multiple departments. Within each care process, there may be work completed by professionals, the patient or through collaborative work of these individuals with or without the patient's family. For professional work, the primary agent is one or more healthcare professionals. Patient work involves the active engagement of the patient. In this thesis, the process of care delivery is being simulated. Simulation will be discussed in detail in Section 1.5. (page 18).

The **posture of care** *task* entails how the body of the nurse twists, turns and bends as well as the hand forces they must use to lift objects. This thesis made use of 4DWATBAK (University of Waterloo), an HF tool to model the care task posture of nurses.

Error is a preventable adverse and potentially harmful outcome of care. The prospect of making an error was significantly increased when nurses work more than 12 hours per shift (Rogers et al., 2004). One small error can lead to catastrophic events (Bridger, 2009). For example, Resnick (2003) reports a patient with blood Type O was transplanted with organs belonging to a donor bearing blood type A (transfusions for blood type O patients can be done only from type O donors). As a result, the patient died of brain damage after the transplant operation a few days later. The root cause analysis concluded that the patient's blood compatibility check was missed, which is the first step when a patient is prepared for surgery. This is a reminder that well-built systems can fail due to human error. Errors are a missing link in this thesis as these are not modeled in the healthcare system unit. A future extension of the research developed from this thesis can be to model error-rates in healthcare.

Tools are objects that HCPs use in delivering care or assisting other HCPs such as lifting devices etc. This thesis does not model tools specifically but the HCP's posture while using these tools are modeled using 4DWATBAK (University of Waterloo), an HF tool.

Work Environment (WE) – Neumann et.al. (2014, p. 1113) describes work environment as "all aspects of the design and management of the work system that affect the employees' interactions with the workplace". WEs are not planned in any organization; they are the product of emergent characteristics that can be classified as unexpected behaviors that arise from the interaction between the components of a work system. WE include: the physical layouts and built environment, supervisory structures, worker interactions, noise, lightning, vibration, temperature, division of labour, use of technology, air quality and management strategies. In the domain of HC, these organizational characteristics can constrain or facilitate professional nursing practice. The Registered Nurses Association of Ontario (2008) reported unhealthy work environments as the basis for the current nurse shortage. Nurse turnover is highly influenced by the WE; a higher workload affects nursing turnover rates and disrupts quality of care and patient safety (McGillis Hall et al., 2005). Poor WEs create overworked nurses that display slower reaction times such as less alertness to changes in patients' conditions, and an increased rate of medication errors that translates into adverse risks to patients (International Council of Nurses, 2015). Positive practice environments are settings that support the personal well-being of staff and maintain good patient care quality standards. A good WE leads to improved productivity of workers (Registered Nurses Association of Ontario, 2008), and can reduce preventable adverse outcomes (errors such as slip, lapses etc.) thereby improving delivery of care to the patient and also address the underlying cause of retaining sufficient qualified nurses (Australia Nursing Federation, 2009). Workload is an intermediate outcome that is impacted by work environment factors. This thesis simulates the work environment of nurses to address nurse workload.

As illustrated in Figure 1**, workload** is one component of the WE. The WE affect the physical and mental workload and can determine the outcomes to be positive or negative for the employees. In the domain of healthcare, workload is the amount of HCP resources (either direct or indirect), needed for a patient per shift (O'Brien-Pallas & Baumann, 1992). Individual patient workload can be summed across all patients of a unit to determine overall HCP workload. Conceptually, workload has several elements to it. Casner & Gore, (2010) define workload in three aspects: a) mental activity; and b) physical burden (biomechanical load and distance walked); c) time pressure. Given the dynamic nature of the nursing work (variability in care task frequency, time and locations), quantifying nurse workload remains a challenge (Arsenault Knudsen, Brzozowski, & Steege, 2018; Neumann et al., 2018). Despite the elusive nature of workload, this thesis quantifies workload.

Excessive workload leads to overtime, absenteeism, presentism accompanied with depression, injuries (including WMSD), burnout, increased error rates, decaying worker morale and performance decrement (Aiken, Clarke, Sloane, Lake, & Cheney , 2008; Aiken, Clarke, Sloane, Sochalski, & Silber, 2002; Alghamdi, 2016; Arsenault Knudsen, Brzozowski, & Steege, 2018; Galletta et al., 2016; Portoghese, Galletta, Coppola, Finco, & Campagna, 2014; Ruotsalainen et al., 2015). There has been a gradual increase in the cost of nurse overtime and absenteeism in Canada from $968 million for overtime and $989 million for absenteeism in 2016 as compared to $860 million and $841 million respectively in 2014 (Canadian Federation of Nurses Unions, 2017c). The International Council of Nurses reports overtime as a common practice in Australia, United States, Europe, United Kingdom and Japan (Australia Nursing Federation, 2009). The number of extra hours worked by Registered Nurses in the United Kingdom increased by 80% in 2012 (International Council of Nurses, 2015). Nurses working more than 12.5 hours were three times more likely to make errors thereby compromising patient safety (Australia Nursing Federation, 2009). Excessive overtime, higher rates of absenteeism and decaying worker morale suggest that the current nurse workload levels compromise quality of care (Canadian Nursing Advisory Committee- Advisory Committee on Health Human Resources, 2002). The Institute of Medicine (IOM) reported that almost all patient safety issues were related to medication errors, overtime and fatigue for healthcare professionals (HCP) (Carayon, 2010). High levels of nurse workload have a direct impact on decision making of nurses and therefore comprises patient safety and the quality of care (Benda et al., 2018). Continuous exposure to high workload environments leads to fatigue. The performance of fatigued workers was found to be on par with alcohol intoxication (Dawson & Reid, 1997). In addition to this, Weigl et al., (2014) reported a negative correlation between workload and quality of care. The scale of these work-related problems suggests that the workload of nurses needs to be better quantified and managed to support quality of care and nurse safety in healthcare systems (Jang et al., 2007). Quantifying nurse workload remains a challenge (Arsenault Knudsen et al., 2018; Neumann et al., 2018). This challenge is addressed in this thesis by developing a proactive 'virtual' tool that can quantify the indicators of nurse workload and quality of care under different technical designs.

1.4.3 Outcomes

As illustrated in Figure 1, the design-oriented approach to using the SEIPS model dictates healthcare outcomes are impacted by workload.

Outcomes are conditions or products that result from the healthcare system and are important indicators of performance. Outcomes can be desirable or undesirable. Proximal outcomes refer to the immediate results of work processes, whereas distal outcomes are those that could emerge after some time (Holden et al., 2013). Outcomes are used to measure the achievement of goals. This thesis measures HCP, patient and organizational outcomes.

1.4.3.1 HCP Outcomes

HCP outcomes include fatigue, biomechanical load, MSD, mental stress, total distance walked and absenteeism. HCP outcomes directly affect the healthcare system (as illustrated in Figure 1); if the mental stress or biomechanical load increases for an HCP then it will lead to a degraded work environment which will inhibit their ability to deliver care precisely. However, if the biomechanical load and mental stress levels of the HCP remain nominal then the work environment will not be degraded, and the HCP may deliver care processes precisely and in a timely manner. The above-mentioned outcomes are inter-related. For example, understaffing can lead to excessive workload giving rise to job stress, fatigue, work-related MSD, absenteeism and eventually burnout or injury. In this thesis, distance walked by HCP, mental stress (average task queue), direct care time and the biomechanical load of HCP, are being examined as HCP outcomes where the HCP is an RN. These outcomes are further described below.

Biomechanical load is the external load that is transmitted through the biomechanical loading of the body. If the tolerance of these biomechanical load forces exceeds the National Institute for Occupational Safety and Health (NIOSH) maximum permissible limit, the tissue may be damaged resulting in discomfort, pain, impairment and even disability in some cases (Nelson, Wickes, & English, 1994). Biomechanical load is affected by the individual anthropometric factors such as age, height, weight, ethnicity etc. This thesis explores the biomechanical load of nurses while performing care delivery under different technical design and operational policies.

Musculoskeletal Disorders (MSDs) are disorders and/or injuries that affect the movement of the human body or the musculoskeletal system such as tendons, muscles, ligaments, discs, nerves, blood vessels, ligaments, joints, cartilage, peripheral nerves and spinal discs etc. (Punnett & Wegman, 2004). MSDs are a global public health problem (Storheim & Zwart, 2014). The MSD risk for healthcare workers is four times higher than manufacturing (Bernard, 1997). In 2014, the

Canadian healthcare system had the highest number of lost time injuries including MSDs (Canadian Federation of Nurses Unions, 2015). The Bureau of Labor Statistics, (2011a) reported nursing as the highest MSD risk industry in United States, with an incident rate of 226 cases per 10,000 employees. In addition to this, MSDs was the leading cause of sickness and absence in Dutch and Greek nurses (Alexopoulos, Burdorf, & Kalokerinou, 2006). In addition to the health of nurses, MSD risk negatively affects the quality of care for patients (Thinkhamrop et al., 2017). A survey of 2,500 nurses by Letvak et al., (2012) reported that medication administration errors increased by 88% because of MSD risk. The leading causes for MSD are excessive work demand and workload, which are a function of biomechanical load amplitude and the duration and frequency of change of load amplitude (Wells, Mathiassen, Medbo, & Winkel, 2007). The Peak and cumulative biomechanical load are the most common MSD risk factors for lower back pain (Kazmierczak, Neumann, & Winkel, 2007; Norman, Wells, & Neumann, 1998). Therefore, this thesis explores the peak and cumulative biomechanical load as indicators of MSD risk.

Fatigue is a phenomenon that results from prolonged exposure to an activity bearing psychological and environmental factors that affect the health (mind and the body) of a HCP (Barker & Nussbaum, 2011). Fatigue is a contributing factor for absenteeism, injury and burnout (Brennan et al., 2013; Davey et al., 2009; Garrett, 2008; Oliva & Sterman, 2001; Registered Nurses Association of Ontario, 2008). Fatigue slows reaction time and increases the risk of errors (Barker & Nussbaum, 2011; Trinkoff, Storr, & Lipscomb, 2001). Continuous exposure to high workload environments results in fatigue and deteriorated (Benda et al., 2018; Weigl et al., 2014). The performance of fatigued workers is on par with working under alcohol intoxication (Dawson & Reid, 1997). This thesis indirectly addresses fatigue in nurses by quantifying physical and mental workloads. MSDs and chronic fatigue are two of the leading causes of nurse turnover (Bureau of Labor Statistics, 2011b; Thinkhamrop et al., 2017; Trinkoff, Lipscomb, Geiger-Brown, Storr, & Brady, 2003).

Mental stress: Davey et.al. (2009, p. 228) defines job stress as "juggling multiple care expectations of various professionals as well as clients". In this thesis, mental stress is addressed using ***task queue*** as it entails the number of pending tasks that a nurse has to complete. The greater the number of pending tasks, the greater would be the mental stress as the HCP would need to finish the current task as early as they can so they can address the pending tasks. Mental stress is indirectly measured in this thesis by quantifying 'task in queue', a mental workload indicator (Potter et al., 2005, 2009).

Total distance walked is the cumulative distance walked by the HCP during one shift. This includes the distances of all the trips made back and forth between the nurse's station and patient beds. In this thesis, total distance walked is being measured in meters and kilometers.

Absenteeism is the lack of the physical presence of an HCP when there is a contractual obligation to be present at a given setting and time (McGillis Hall et al., 2005). In 2014, 21,000 RNs were absent each week due to an illness or disability which leads to a cost of $846.1 million in replacements (Canadian Federation of Nurses Unions, 2015). **Burnout** is a syndrome of cynicism and emotional exhaustion (Maslach & Jackson, 1981). Furthermore, The Manitoba Nurses Union (2015) have stated that over 71% of the nurses they interviewed have faced burnout at least once. Absenteeism and burnout are usually caused by exposure to high work demands and workload that lead to higher amounts of job stress, fatigue and MSD (Davey et al., 2009). This thesis indirectly addresses absenteeism and burnout by quantifying the workload and work demands of nurses.

Direct care time represents the actual time spent by the HCP delivering care. This excludes documentation and walking inside the unit. In industrial engineering, this is called value-added time. In this thesis, direct care time for nurses is quantified.

1.4.3.2 Patient Outcomes

Quality of care: Quality in terms of healthcare is delivering the right care to the right patient at the right time – every time. Quality of care is the assessment of care services provided to the patients. Campbell, Roland and Buetow (2000) defined two aspects of quality of care: 1) the accessibility to the healthcare system; and 2) the actual care that is given (i.e. effectiveness of the processes of care). The primary responsibility of a nurse as a professional HCP is to deliver care to patients. There are certain work environment factors that assist or inhibit the nurse in carrying out this responsibility such as, nurse-patient staffing ratio; the physical layout of the unit; and the acuity of patient. These factors directly contribute to nursing workload that then impacts the quality of care provided. In this thesis, indicators of quality of care are measured using 'missed care', 'missed care delivery time', 'percentage division of missed care' and 'care task waiting time'.

'Missed care' is defined as the number of pending tasks that were not started by the nurse before the end of the shift. 'Missed care delivery time' is a potential indicator of overtime. It signifies the additional time a nurse must stay behind to perform these care activities. In some cases, the next nurse has to perform these care tasks that were not completed before the end of shift, in addition to the care tasks from their own shift. 'Percentage division of missed care' signifies what percentage of care tasks that are high priority such as medication, vital signs, etc., and low priority tasks such as documentation. In this thesis, these indicators of 'missed care' are quantified using simulation and validated by means of the MISSCARE survey tool (Kalisch & Williams, 2009). 'Care task waiting time' is the average time a patient must wait before receiving a scheduled or unscheduled care task.

Patient satisfaction is a very common performance indicator for quality in the domain of healthcare and refers to the level of satisfaction perceived by a patient in an healthcare environment after or during receiving care. However, this thesis does not measure patient satisfaction.

1.4.3.3 Organizational Outcomes

Organizational outcomes measure performance that reflects quality, cost, reputation and achievement of mission and goals. Organizational outcomes for the proposed studies include overtime and organizational culture.

Overtime refers to the number of hours an HCP must work beyond the scheduled limit (McGillis Hall et al., 2005). While the Ontario Ministry of Labor (2017) has mandated that overtime starts after 44 hours of work per week; overtime for nurses is considered as any additional work beyond their scheduled shift. For example: staying an hour or two to complete their work (McGillis Hall et al., 2005). In 2014, 19,383,900 hours of overtime were reported for nurses in Canada, which is equivalent to 10,700 fulltime positions at an estimated cost of $871.8 million dollars (Canadian Federation of Nurses Unions, 2015). Overtime not only affects the organizational outcomes, it in-directly affects patient outcomes and HCP outcomes Australian Federation of Nurses (2009) reports that the prospect of making an error increases significantly after working for more than 12.5 hours, thereby compromising patient care quality. Excessive overtime leads to higher rates of absenteeism and decaying worker morale (Canadian Nursing Advisory Committee- Advisory Committee on Health Human Resources, 2002). Excessive overtime is an outcome of an unhealthy WE. This thesis indirectly measures overtime by quantifying 'missed care' and 'missed care delivery time'.

Organizational culture is a shared concept between coworkers in an organization which includes values, attitudes, beliefs, and norms that are felt in a certain way by all members. This thesis does not measure organizational culture.

In summary, the conceptual model of this thesis builds on a more design-oriented approach of the SEIPS 2.0 model. This design-oriented approach takes into account HF at a systems level. As illustrated in Figure 1, the 'design' section entails the technical design and operational policies of the healthcare such as nurse-patient ratio, patient acuity, geographical-patient bed assignment etc. These policies impact the healthcare unit system that consists of the HCP, the process of care delivery and care task postures, and the work environment. Workload is an emergent outcome of the healthcare system design that effects HCP, patient and organizational outcomes. HCP outcomes also affect the healthcare system unit. Therefore, workload needs to be better managed. One approach to manage workload for nurses is through the changes in the system design policies by better managing the drivers of workload.

1.5 The Need for Simulation

Current approaches to testing design and management decisions such as the real-life trial and error methods can be very expensive and hazardous (Gaba, 2007), as workers would be exposed to unsafe and untested environments that can not only affect their health but also negatively impact productivity and process efficiency with possible long-lasting consequences. Simulation allows faster testing of newer technical design and operational policies at less cost without the risk of exposing workers into unsafe and untested work environments. Simulation allows the researcher to gain proactive insight and test the impacts of multiple scenarios, explore interactions of multiple resources and technical design policies. Hence, there is a need for a tool that can 'virtually' assess and predict the effects of design and policy changes on HCP and patients without the risk of real trials or at the expense of HCP's health. Simulation is a potential solution to this challenge.

1.6 Solution Pathway: Simulation Technologies

Simulation is the process of 'virtually' representing the demonstration of a real-world system (Banks, Carson, Nelson, & Nicol, 2005). The tools used for simulation are categorized as simulation technologies. Simulation in the domain of healthcare has mainly been done for three purposes – training and education, research and assessment for the facilitation of patient-safety (Brazil, Purdy, & Bajaj, 2019). With the help of design-level tools of simulation, ergonomists can obtain a better understanding of the impact of various alternatives proposed for a change in the system. Design level tools allow early-stage application of ergonomics where costs are lower and solution options are greatest (Bridger, 2009). Due to recent development in the domain of healthcare, process simulation models are being conceived that can ultimately lead to leaner processes bearing improved performance analytics (Rosen, 2008). Simulation in the domain of healthcare span a range of activities such as training, analyzing error and related causes, work environments, etc. These all share the common purpose of improving quality of care, safety of the HCP and the efficiency of healthcare services (Casier, Casier, Ooteghem, & Verbrugge, 2012). Examples of ergonomic tools are described below.

1.6.1 Medical Simulators

Medical Simulators are simulation technologies that educate and train medical professionals. It has been used by surgeons or medical trainees as a rehearsal before a complex or major surgery to improve the dexterity and precision (Rosen, 2008). In this thesis, medical simulators are not being used.

1.6.2 Computerized Simulation

Computerized simulation imitates real-world scenarios over time (Banks et al., 2005). These are well suited for analyzing interactions of variables in a complex system such as products, raw materials and workers in a factory or, patient beds and HCPs of a hospital and predicting possible outcomes. Some commonly used techniques include: Digital Human Modelling (DHM), Agent-Based Modelling (ABM), System Dynamics (SD) and Discrete Event Simulation (DES). These are further described below.

Digital Human Modelling (DHM) is the process of developing a digital human model using biomechanical and anthropometric databases, of the human body using anthropometric data and it's interaction with the environment (Chaffin, 2007). A variety of biomechanical tools are available to assess workload which includes observational tools such as REBA (Rapid Entire Body Assessment), RULA (Rapid Upper Limb Assessment), Posture, activity, tools, and handling (PATH) etc. (Takala et al., 2010) and digital human modelling approaches (Bridger, 2009; Dode et al., 2016; Kazmierczak et al., 2007; Zhang et al., 2013). While observational tools are commonly used in the service industry, DHM quantifies the biomechanical load of postures proactively; and is a widely used tool in the service industry. Similar to observational tools, DHM is also used for ergonomic evaluation of a workstation or a product. The difference is that this process is more 'virtual', complex and more dynamic. DHM is often used to create environments using computer-aided design (CAD) software. Some DHM software tools include: Jack 2.0 (Siemens), allows the creation of models (virtual humans) belonging to different population groups. Users can test design solutions for humans with different physical characteristics. HF elements such as injury risk, the ability to fit and reach, biomechanical loads and line of sights can be calculated. Other software such as 4DWATBAK (University of Waterloo), is a risk-validated tool that is used to calculate the biomechanical load of humans belonging to different population groups. DHM has been used in healthcare. Zhang et al., (2013) used DHM to address vision and fitting issues for basic nursing care tasks. Hanson et al., (2009) explored the range of motion for caregivers and caretakers for bathing system design. Paul & Quintero-Duran, (2015) explored lower-back pain for nurses for a hospital bed pushing task. DHM fails to report the time sequence of care tasks. While most of the research is done in manufacturing, there is a research gap for predicting MSD risk in healthcare. Manufacturing is mostly cyclic work and is relatively easier to model while healthcare is much less cyclic and more complex with increased variation. Lacking in most tools is ability to assess/review workload over time which allows cumulative aspect of workload to be predicted and more realistic monitoring of worker exposures. DHM is good for single instants, less so for irregular complex work. It does not provide the task sequence. Therefore, tools are needed that can provide task sequence. This thesis makes use of DHM to provide quantifiable measures of peak and cumulative biomechanical load, as a means to quantify the MSD risk for nurses.

The following are some of the popular simulation tools that can provide task sequence:

Agent-Based Modelling (ABM) is based on a collection of autonomous decision-making objects called agents, which individually assess their situations and make decisions rooted in given rules

(Barnes, Morgan, Pineles, & Harris, 2018; Cabrera, Taboada, Iglesias, Epelde, & Luque, 2012). Kiani (2016) reports that due to the complex and highly controlled environment of healthcare, ABM is not well suited for healthcare interventions as compared to other techniques like discrete event simulation (DES). Therefore, in this thesis, ABM was not used.

System Dynamics (SD) addresses the complexity and structures of a dynamic system. This involves the development of simulation models that portray processes of complex problems using continuous feedback loops that can be tested systematically to find effective strategies for incapacitating resistance to change in policy, improve policies and organizational designs and assessment of training effectiveness (Jiang, Karwowski, & Ahram, 2012; Oliva & Sterman, 2001). SD is highly capable of addressing healthcare issues, but it operates at the organizational level and is less suited for simulating processes occurring at the system or unit level. Jiang et.al., (2012) used SD for the assessment of training performance effectiveness, this study operated at the organizational level. Farid (2017) explored the effect of HF on nurses' health and quality of care. This research aims to simulate the process of care delivery at the unit level. Therefore, SD was not used in this thesis as it is ideal for the simulation at the organizational level.

Discrete Event Simulation (DES) is the process of representing complex structures of a system/unit as a sequence of ordered events and stages, in which the variable(s) change at a discrete set of points (Banks et al., 2005). DES is an operational research technique used to assess and predict the efficiency of a proposed or an existing system (Jun, Jacobson, & Swisher, 1999). It is a tool used to get a better outlook on the problem and is ideal when multiple system resources are present as it provides the researcher with the option of studying one or more different scenarios separately and in great depth by changing inputs and to observe its effects to get a valuable insight (Banks et al., 2005; Schmidt, Geisler, & Spreckelsen, 2013). DES allows researchers to compare feasible solutions and choose the best optimal solution closest to real-world scenarios (Perez, 2011). Furthermore, there is evidence demonstrating DES to be a successful tool with several applications in manufacturing and in the service industries. DES has been effectively used for the analysis of system design alternatives, business modelling, cost evaluation and optimization of resources (Günal & Pidd, 2010). Iwataa and Mavrisa (2013) conducted a study on the operations and support activities of aerospace vehicles. DES was used to get better solutions i.e. reduce cycle steps and cost. Fatemi et. al (2008) reported a study on "Sense and Avoid" problems of an unmanned aerial vehicle. Dode (2012) used HF modelling and

DES methodologies in the engineering design processes to incorporate fatigue dose and learning curves. Similarly, Perez et al. (2014) created a biomechanical model using DES modelling to deliver patterns of work cycle load-time over the shift i.e. fatigue-time history. DES is widely used and has had significant success in fields like industrial engineering, aviation, business modelling, manufacturing and service industry (Günal & Pidd, 2010). DES allows modelling at the systems/unit level, which is ideal given the conceptual model for the proposed research. Therefore, DES is a potential tool to analyse changes in healthcare unit design parameters on HCP wellbeing and quality of care at the system/unit level.

1.7 Discrete Event Simulation (DES) in Healthcare (HC) Systems

There has been significant research published regarding the application of DES in the domain of HC. An overview of examples of DES is described below.

1.7.1 Hospital units and Clinics

DES has been widely used to model hospital units such the operating room, intensive care unit (ICU), pediatric ICU, laboratory, pharmacy and maternity units (Günal & Pidd, 2010; Mohammadi & Shamohammadi, 2012). Swisher and Jacobson (2002) evaluated the design of two family physician practice clinics using DES. These studies provided insight into the problems and help managers conceive better solutions. In this series of research studies, the in-patient unit of a hospital is being simulated.

1.7.2 Hospital flow optimization

Healthcare facilities are currently utilizing DES tools for hospital flow optimization. DES has the potential to improve existing processes by easily testing new strategies before actual implementation. Casier et al. (2012) used DES to optimize patient data and supply flows over an existing hospital process by evaluating key performance indicators. DES helped hospital managers understand the adverse effects when a change was planted in the system. The use of DES allows hospital managers to examine the benefits of new strategies without risks to patient safety. DES has also been used to improve cost efficiency in worker scheduling and improve patient flow. (Günal & Pidd, 2010; Jun et al., 1999; Reid et al., 2005). This thesis does not test hospital flow optimization.

1.7.3 Patient wait times

Komashie & Mousavi (2005) modelled the operations of an emergency department to understand the system behavior and examine the causes of excessive waiting times. DES served as a tool for assessing the impact of major departmental resources on key performance indicators. It served as a cost-effective method for testing various what-if scenarios for possible system improvement. Duguay & Chetouane (2007) conducted a study on the design of an emergency system to understand injury levels of healthcare workers. In this thesis, patient wait times are being measured indirectly by quantifying the task in queue time.

1.7.4 Nursing workload

Little attention has been given to measuring nurse workload using DES. Baril et.al. (2016) studied nursing workload and patient wait times in a Québec based haematology-oncology clinic using DES. It was observed that the patient waiting time was not too long but the nurse occupancy (staffing) rate was high in the morning and low in afternoon i.e. 87% and 64% respectively. New appointment scheduling methods were formulated that resulted in more efficient nurse staffing to match patient demand. Lebcir et al. (2017) used DES to indirectly measure workload by modeling the treatment of Parkinson's disease patients. Theses techniques have been limited to modelling patients as a 'production' flow system. There is a research gap – a scarcity of published research work that models the process of care delivery of nurses to quantify nurse workload using DES. This thesis addresses this gap by using a HCP focused approach to developing a tool that can be used to better manage nurse workload by quantifying the impact of changing technical design and operational policies on nurse workload and quality of care.

1.7.5 Physical Layout

Spatial layout is a direct contributor to productivity and efficiency (Boucherie et al., 2012). Using generalized DES models, managers can predict the effect of different layouts of a hospital unit in term of nurses' movements (Choudhary et al., 2010). Similarly, Boucherie et.al. (2012) illustrated the potential of using DES for the design of a new health care facility. In this proposed series of research studies, the physical layout is being used as a design parameter.

1.8 The Missing Link

While there has been significant DES research published in the domain of HC, these studies have generally been limited to modelling from the perspective of a patient where a patient is modelled in a fashion similar to modelling product flows in production systems. There is a scarcity of research focusing on nurse workload and care quality, despite the fact that nurses deliver 75% of the care in hospital settings (Nursing Task Force, 1999). HF has been missing from most of DES efforts. In addition, there has been a scarcity of published work analyzing HCP workload and quality of care. Testing the application of DES with a focus on the HCP is a novel approach. Most efforts at using DES with a human-centred approach to date have been focused in manufacturing such as using DES to study the system performance, productivity and worker wellbeing (cumulative biomechanical load) in serial-flow car disassembly, and studying human-fatigue recovery and quality in electronics assembly lines (Dode et al., 2016; Kazmierczak et al., 2007).

In summary, hospital processes need to improve in safe ways. Design decisions contribute to creating a safe and efficient WE. Workload is one component of WE. Therefore, when the work environment degrades and Workload increases, there is a direct impact on the health of HCP. Since nurses deliver over 75% of the care (Nursing Task Force, 1999), any effect on the nurses' health will have a direct impact on the quality of care. Hence, tools are needed to understand and test the impact of changes in the work environment on nurse and patient outcomes. Since most HF tools are systems-based and user-centered approaches, HF informed models and tools can serve as viable options to test and design changes in the healthcare units. To test this conceptual model, DES has the potential to predict the effects of changes on nurse and patient outcomes. DES is an ideal tool to analyze hospital processes that are complex, interconnected processes that occur at the system/unit level.

1.9 Objective of the research

The aim of this research is to create a novel, adaptable modelling approach that can proactively test and quantify the impact of different technical design and operational policies, on nurse outcomes and patient outcomes. In this thesis, a tool that can simulate the process of care delivery of nurses is developed using a novel nurse-focused approach to DES modeling. Previously, DES has been used to model patients as a 'product flow' in a production system. The modelling approach developed will provide decision-makers a new tool that integrates existing evidence to provide insight into the long-run performance trends resulting from their operational decisions. These series of research studies address the need of focusing on HCP to improve the healthcare system, outlined in editorial of the special issue: 'Ergonomics and Human Factors in Healthcare System Design' in IISE (Institute of Industrial and Systems Engineers) Transactions in Occupational Ergonomics and Human Factors (Neumann et al., 2018). More importantly, this multidisciplinary research serves as a response to the need for a tool that can better manage the poor work demands and workload of nurses (National Advisory Group on the Safety of Patients in England, 2013).

This research will answer the following question:

Primary RQ – *How can the effects of changing the technical design and operational policy parameters on nurse outcomes and patient outcomes, be quantified using human factors enabled discrete event simulation?*

To answer the main RQ, the following specific questions have been formulated that will be answered using a DES model. This model imitates the care processes and layout of an in-patient unit of a hospital. Each RQ extends the model's capability and tests different design patterns.

RQ1 – *How do changes in nurse to patient ratio (NPR) affect indicators of nurse outcomes and patient outcomes?*

As illustrated in the conceptual model (Figure 1), the design changes directly affect the healthcare unit system, which impacts the nurse outcomes and patient outcomes. In RQ 1, the design changes are Nurse- Patient ratio (NPR); Nurse outcomes are distance walked and task queue, and patient outcomes are missed care and waiting times. RQ 1 is addressed in Chapter 2

RQ 2 – *How do changes in patient acuity and NPR impact indicators of nurse and patient outcomes?*

RQ 2 extends the model's capability by exploring the interaction of patient acuity and nurse-patient ratio by means of a sensitivity analysis. In addition to the patient and nurse outcomes in RQ 1, newer outcomes are also explored. For nurse outcomes, 'direct care time', for patient outcomes, 'missed care delivery time', are explored. RQ 2 is addressed in Chapter 3

RQ 3 – *How can this nurse-focused DES tool for in-patient care unit be validated?*

RQ 3 validates the approach of creating 'valid' nurse-focused DES model. The nurse-focused DES model provides validation on three fronts: i) 'external validation' by means of a field study, ii) in-data validity, iii) 'internal validation'. RQ 3 is addressed in Chapter 4.

RQ 4 – *How do changes in geographical patient-bed assignment impact the distance walked by the simulant-nurse and other indicators of nurse and patient outcomes?*

RQ 4 is used to quantify the impact of different geographical patient-bed assignment on nurse and patient outcomes using the DES model created from the validated approach in RQ 3. RQ 4 is addressed in Chapter 5

RQ 5 – *What are the biomechanical loads encountered by nurses while performing daily tasks in an inpatient unit and what are the time trace of the biomechanical loads for these nursing care tasks over a full shift, using a combination of DES and DHM?*

RQ 5 uses DHM to model the various postures of a nurse while delivering care. These postures are modelled by means of a video-recording study where the nurse will mimic all care postures. The biomechanical load obtained using DHM, will be used as inputs to the DES model, to create a time trace of biomechanical loads for a shift in nursing. RQ 5 is addressed in Chapter 6

RQ6 – *How do changes in patient acuity, geographical patient-bed assignment and nurse-patient ratio affect the biomechanical loading in nurses and other indicators of nurse and patient outcomes?*

Using the modeling capability developed in RQ6, the DES model will quantify the impact of patient acuity, geographical patient-bed assignment and nurse-patient ratio on the peak and cumulative biomechanical load of nurses and other indicators of nurse outcomes and patient outcomes. RQ 7 is addressed in Chapter 6.

A detailed description of how these research questions will be addressed, are mentioned in upcoming chapters.

CHAPTER 2

PILOT SIMULATION MODEL

In this chapter is a discussion of the initial creation and testing of a novel nurse-focused DES modelling approach that could proactively assess the quality of care and the workload for nurses, by modelling the delivery of care for patients under different technical design and operational policies. Specifically, the demonstrator model quantified the effect of changing nurse-patient ratios on Quality of Care and nurse workload. The emphasis here is on the development of an adaptable content sensitive method, rather than a definitive general answer to a specific scenario of interest to a stakeholder.

This chapter address RQ 1 – *How do changes in nurse to patient ratio (NPR) affect indicators of nurse and patient outcomes?*

2.1 Methods

The computerized simulation model was created using a commercial DES environment software (Rockwell ARENA). The DES is the representation of the HCP's work processes. The demonstration model was created in consultation with a subject specialist – a Registered Nurse with extensive research and practical experience.

As illustrated in Figure 2, the inputs of the model consist of patient care data, operating logic and virtual layout. The outputs consist of *task in queue time* and *missed care*, used here as care quality indicators and, *task queue* and *cumulative distance walked* as nurse workload indictors. These are further expanded upon in the next section.

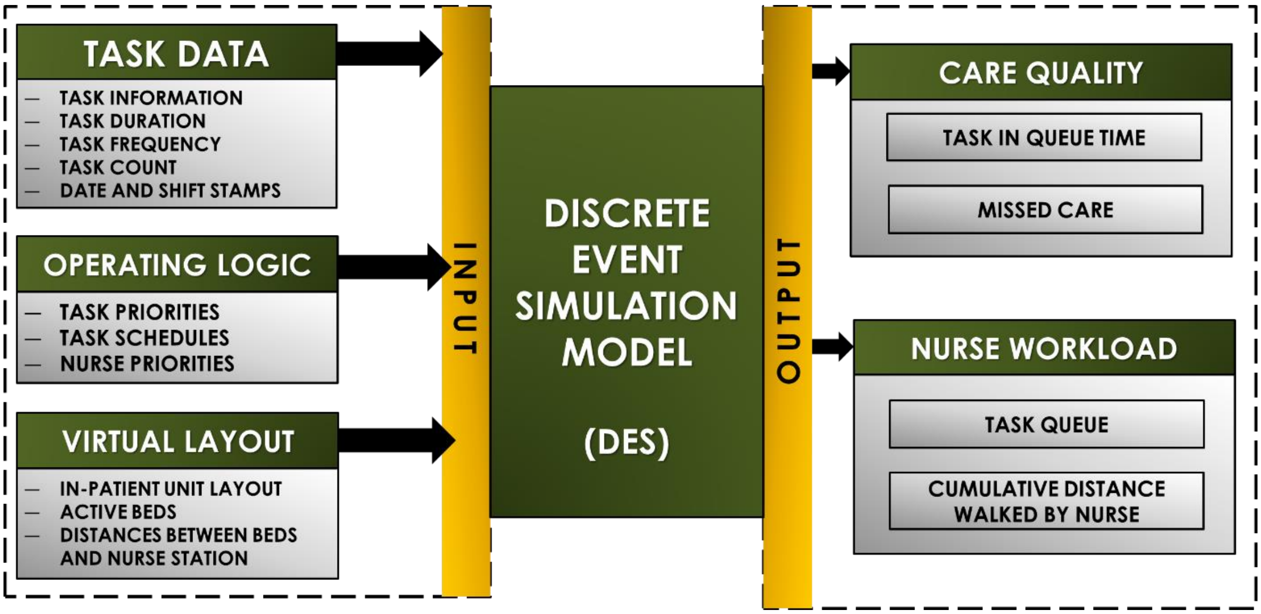

Figure 2 illustrates the Inputs and Outputs of Pilot DES model. Inputs are Patient care data, Operating Logic and Virtual layout, and Outputs to the model are Quality of Care (Task in Queue time, Missed Care) and Nurse Workload (Task Queue and Cumulative Distance walked).

2.2 Model Inputs

2.2.1 Patient care data

As illustrated in Figure 2, patient care data entails essential details of the daily patient care tasks that a nurse performs. This data was obtained from a neurological in-patient unit for a period of one month from an inpatient unit of a large urban academic health centre in Canada for a period of one month. The data was part of a workload report generated from the hospital's Infor Healthcare software system, formerly GRASP (Grace Reynolds Application of the Study of PETO) (Farrington, Trundle, Redpath, & Anderson, 2000; Song et al., 2004). GRASP is a proprietary management information-processing system used to collect data for analysis of nursing workload. Data contains information pertaining to the patient care tasks that were performed by nurses. The definitions of each task are specific to GRASP methodology e.g. assessment refers to the completion of the Braden Scale, Morse Fall Assessment, etc. and does not refer to the ongoing assessment that nurses conduct when delivering care. Data is manually entered by nurses at the end of their shift. For each sub-task (such as: IV Maintenance) there is a pre-set standardized time duration. Approximately 70% of the hospitals in Ontario use the Infor healthcare (GRASP) system

(Song et al., 2004). In United States, Infor is used by 72% of the hospitals (Infor, 2016). Patient care data is comprised of *task information, task frequency* and *task duration.* i) *Task information* includes basic task information such as task group, for instance nutrition; sub-tasks within this category include feeding with minimal assistance; shift and date stamp. ii) *Task frequency* entails how frequently a certain task is completed along with the day and time stamps. Task frequency was calculated using an average of the task count for each task group across all patients per day for a period of one month. iii) *Task duration* is the amount of time required by the nurse to complete the task. Task duration for each of the task groups was calculated using a frequency-weighted average of GRASP's standardized time duration for all sub-tasks of in a Task group. Since the GRASP system uses a standardized time duration for each sub-task, a frequency-weighted average was used in this research to reduce the volume of sub-task programming in the model. Table 1 contains the cumulative time durations of the tasks for the DES model.

2.2.2 Operating Logic

As illustrated in Figure 3, the model's operating logic of the DES model consists of *task priorities, nurse priorities, task schedules, task location* and *call tasks*. These were developed in consultation with the subject matter expert using the GRASP-specific definitions for each task. It is anticipated that nurses may assign a different priority than those listed in Table 1 and the investigators are currently working with a nursing team to explore and refine this logic in a field study. The modelling method itself allows for testing of the potential impacts of different task prioritization strategies. *Task priorities* indicate which tasks have an increased priority for completion relative to other tasks in queue. *Nurse priorities* can also be referred to as the 'brain of the simulated nurse' – the logic rule identifies which task a nurse performs with respect to the task priorities. In the demonstrator model presented in this chapter, the simulated nurse is programmed to do the highest priority task first. There may be occasions where more than one task bears the same priority. In this case, the task logic was built to direct the simulated nurse to perform the task for the closest patient (at the least distance). Figure 3 represents the *operating logic* of this model.

Table 1: List of tasks programmed in the DES model. The list contains the task name along with their respective priority levels, task schedule type and time duration where 1=highest task priority. Time duration for each task group is calculated using a frequency-weighted average of the sub-tasks for each group, as reported by GRASP systems.

Task Group	Priority level (rank)	Task schedule type	Task delivery location	Time Duration (min)
Medication	1	Random intervals	Bed side	6.51
Vital Signs	2	Random intervals	Bed side	5.26
Assessment and Planning	3	Random intervals	Bed side & Nurse Station	6.93
Vascular Access	4	Random intervals	Bed side	31.50
Treatments	5	Random intervals	Bed side	9.50
Activity *(Patient lifting tasks such as: Place patient on stretcher)*	6	Random intervals	Bed side	26.10
Consultation	6	Random intervals	Bed side	6.00
Hygiene	6	Random intervals & Scheduled interval (8:00AM)	Bed side	13.32
Nutrition	6	Random intervals & Scheduled intervals (8AM, 12PM, 5PM)	Bed side	17.05
Other Direct Nursing Care	6	Random intervals	Bed side	25.65
Admission	6	Scheduled interval (7:30AM)	Bed side	32.10
Discharge	6	Scheduled interval (7:30AM)	Bed side	21.40
Evaluation	6	Random intervals	Bed side & Nurse Station	3.00
Non-patient care	6	Random intervals	Bed side & Nurse Station	13.79
Elimination	7	Random intervals	Bed side	19.91
Teaching and Emotional Support	8	Random intervals	Bed side	19.68

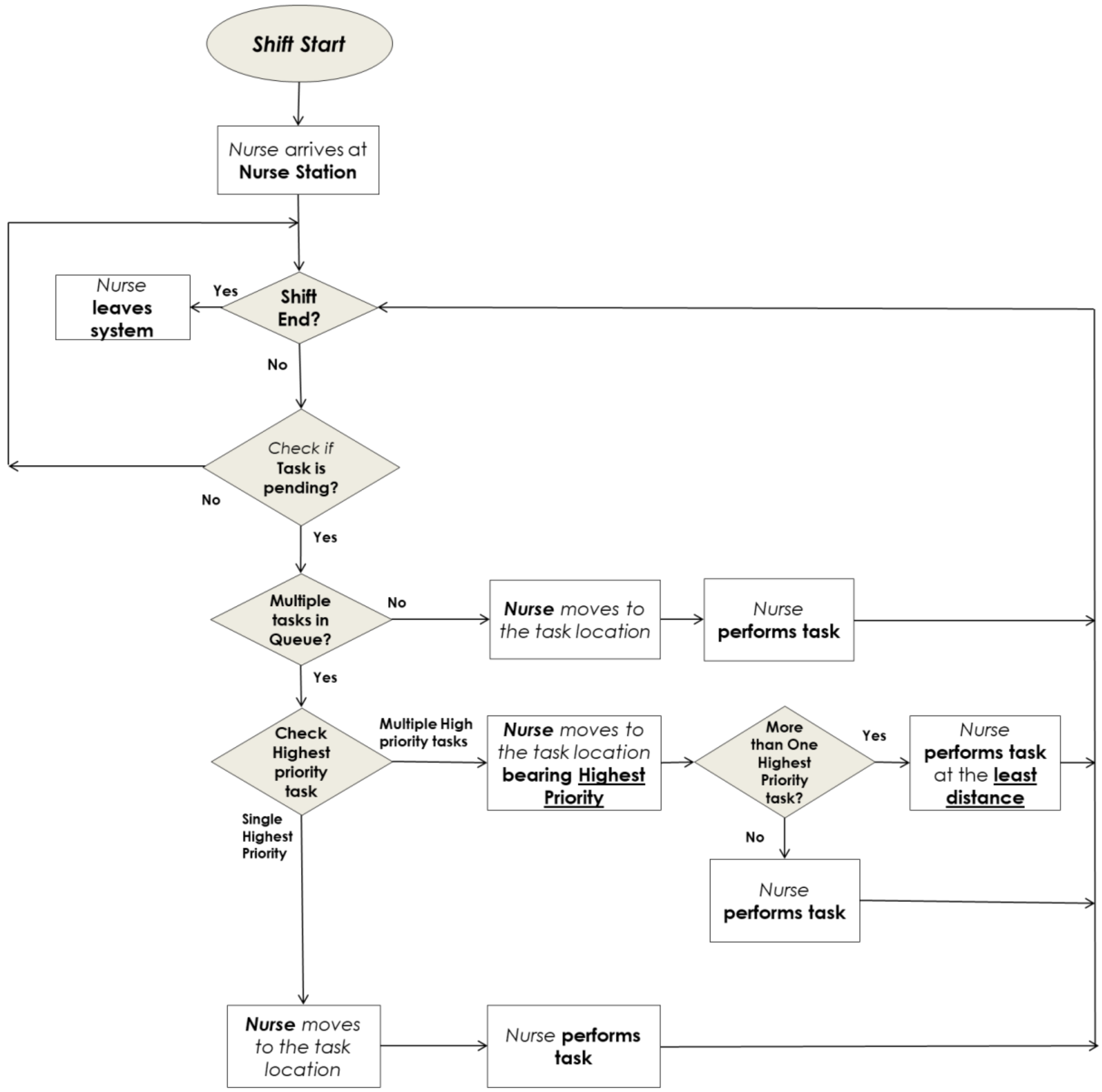

Figure 3 illustrates the flow chart representing the operating logic of the Discrete Event Simulation (DES) model

As illustrated in Table 1, *Task schedule* refers to tasks that follow either an established schedule or those that occur randomly throughout the shift, or both. For example: Hygiene is scheduled for once a day. However, the hygiene task can happen at any time (randomly) as well as the need arises. In this model, nutrition, hygiene, admission and discharge are identified as both, scheduled and random tasks. Within the simulated environment, there are also '*call' tasks* that are called directly by the patient. For example: within the task group of Vascular Access, a patient's IV may become blocked. Therefore, the nurse performs IV maintenance, a task that was not scheduled or a random task but in fact this was a task that was called directly by the patient. The

Task location was determined for each task i.e. occurring at the nurses' station or patient bedside. *Task priority level* and *task scheduling* for the DES model are listed in Table 1.

To test the ability to simulate the process of care delivery using flow simulation (DES), the demonstrator model was created from different sources, such as, patient data was taken from a neurological unit; subject matter expert was from medical-surgical unit; unit layout was built from a hospital layout manual. Using data from different sources, may compromise the quality of modeling outputs.

2.2.3 Virtual layout of the Discrete Event Simulation (DES) model

The virtual layout was developed using Microsoft Visio software to define the overall floor plan details of an inpatient unit such as the nurse station location, total beds and the distances reflecting the simulated unit layout in the DES model. The virtual layout is also used for visual verification while running the simulation. It allows the software to display the nurse's movement on the layout diagram, that helps to visually verify the simulated-nurse's movement patterns during simulation trials.

2.3 Outputs

In this demonstrator simulation model, nurse workload is assessed by *task queue*, a mental workload indicator representing the number of pending tasks which has been associated with medical errors (Potter et al., 2009). Tasks are generated stochastically by the model according to the frequency and schedule of the unit's historical GRASP data (per 2.1). These tasks are recorded in a sequence/queue as a "stack" for the simulated nurse to perform according to the task priority rules, this stack is called the task queue. *Cumulative distance walked by nurse*; the total distance walked by the nurse during a shift in metres. Quality of Care is assessed by calculating *task in queue time*, the average amount of time a task has been in queue waiting to be completed, and by calculating the amount of *missed care*, the number of pending tasks that were not started by the nurse before the end of the shift. In practice, many of these tasks will not be "missed", as the simulation indicates, but they may be handed over to the next nurse in real-life or the present nurse must work overtime to complete these. Since this DES model is only modelling day shifts therefore, these missed care tasks are not rolled over to the next shift.

2.4 Demonstrator Model Testing

NPR is defined as the number of patients assigned to a nurse. The DES model was simulated on different NPR conditions: Low (1 nurse: 2 patients), Medium (1:4), and High (1:6), each for a period of 252 shifts which is approximately the total working days in an year. Each shift consists of 12 hours which is the standard shift length in nursing for North America. Data for 10 replications were recorded for each operating condition to calculate warm up period for the model and to analyse 10 years of nursing data for each operating condition. Warm up times are used in simulation for the model to reach an optimal operating state. For this model, a warm up period of 41 days was established using Welch's method (Hoad, Robinson, & Davies, 2008); Averages across shifts were taken for *missed care, task in queue time, task queue* and *cumulative distance walked*.

2.5 Results

A nurse focused DES modelling approach was developed, the DES, that demonstrated the ability to assess the impact of changing nurse-patient ratios on Quality of Care and nurse workload. The demonstrator model exhibited that as the NPR increased (Low, Medium, High), nursing workload increased (*tasks in queue*: 2, 15, 33 tasks respectively; *cumulative walking distance*: 279, 269, 595 meters respectively) and Quality of Care deteriorated (*missed care*: 17, 24, 53 tasks respectively; *task in queue time*: 0.3, 1.0, 1.2 hours respectively). A summary of these results are presented in Table 6.

Table 2 illustrates the results for Quality of Care (missed care, task in queue time) and Nurse workload indicators (task in queue time, cumulative walking distance)

Nurse Patient Ratio (*NPR*)	**Quality of Care indicators**		**Nurse workload indicators**	
	Missed Care (*no. of task*)	**Task in queue** Time (*hours*)	**Task in Queue** (*no.* of *task*)	**Cumulative Walking Distance** (*meters*)
Low (1:2)	17	0.3	2	279
Medium *(1:4)*	24	1.0	15	269
High *(1:6)*	53	1.2	33	595

2.5.1 Nurse Workload Indicators

As illustrated in Figure 4, the demonstrator model showed an increase in the number of *tasks in queue* by 120% when the NPR is increased from medium to high and decreased by 86% when NPR levels changed from medium to low. However, the *cumulative distance walked* increased in both cases i.e. when the NPR is increased from medium to high and medium to low by 110% and 3% respectively. With the increase in NPR (Low, Medium, High), nursing workload increased in terms of *task queue* by 2, 15, 33 tasks respectively, and *cumulative distance walked* by 279, 269, 595 meters respectively.

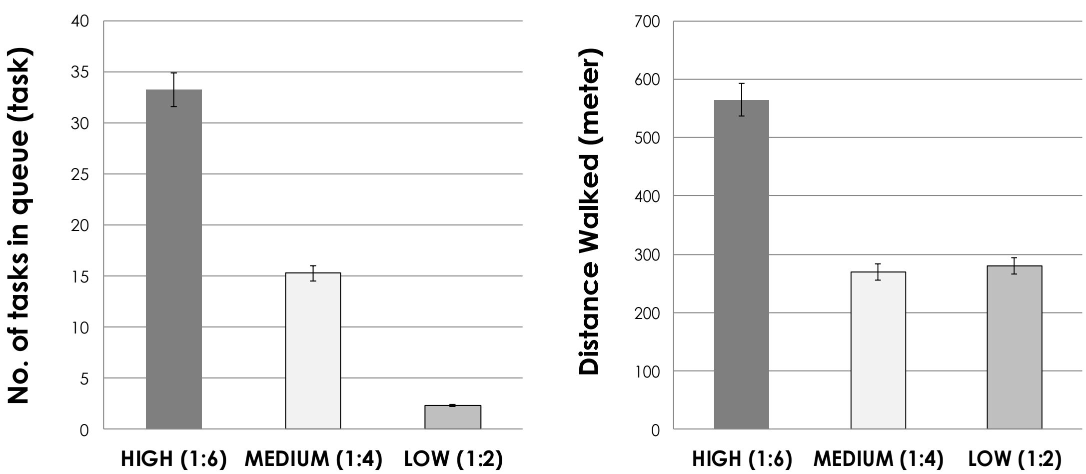

Figure 4 represents the Nurse Workload indicators: Mean and St. Deviation of 'No. of Task Queue' (left) and 'Distance walked by Nurse' (right)

2.5.2 Quality of Care Indicators

As illustrated in Figure 5, the demonstrator model shows an increase in missed care by 120% when the NPR is increased from medium to high. Missed care decreased by 86% when NPR levels changed from medium to low. Furthermore, *task in queue time* increased by 20% when the NPR is increased from medium to high and *task in queue time* decreased by 70% when NPR levels changed from medium to low. With the increase in NPR (Low, Medium, High), Quality of Care deteriorated–*task queue time* increased by 0.3, 1.0, 1.2 hours and *missed care* increased by: 17, 24, 53 tasks respectively, respectively.

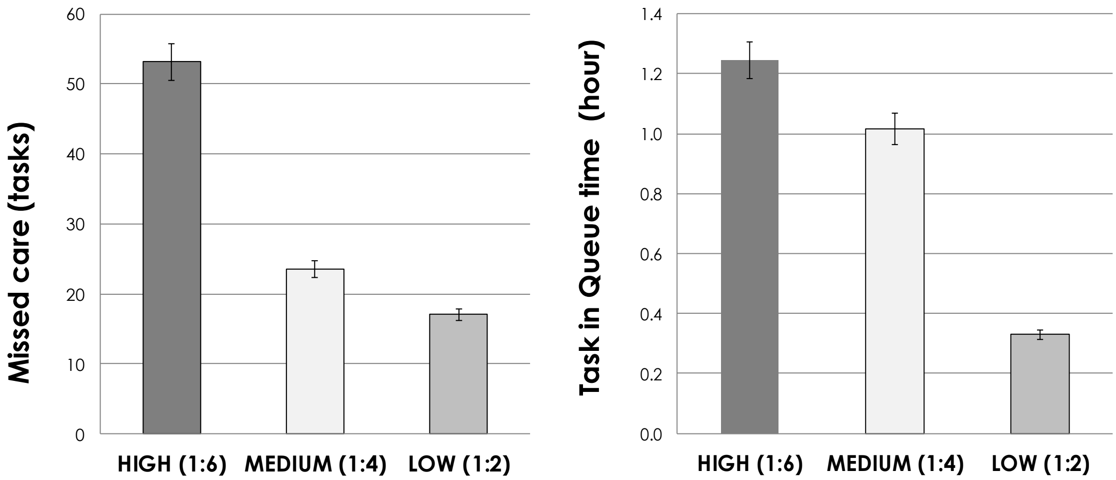

Figure 5 represents the Quality of Care indicators: Mean and St. Deviation of 'Missed care' (left) and 'Task in Queue time' (right)

2.6 Discussion

In this chapter, a nurse focused DES modelling approach was developed, to evaluate the impact of healthcare system design policy choices on nurse workload and care quality. This is a novel approach in DES as previous simulation studies have only focused on modelling patient flow.

The top three missed care tasks reported in this international RN4CAST study conducted in medical and/or surgical units of 488 hospitals across 12 European countries (Ausserhofer, Zander, Busse, Schubert, Geest, et al., 2014) were comfort/talking, care planning and patient education. These were found consistent with the most prevalent areas of missed care identified by the simulated model ('teaching and emotional support' and 'assessment and planning'). Therefore, the simulation model was able to demonstrate similar results regarding the types of missed care adding to the validity of this first test of DES. The quantity of missed care in the simulated model is much larger (17-64 missed care tasks) than reported in the RN4CAST study (range of 1.5-7.5 and mean of 3.6 missed care tasks). One possible explanation is that the simulated model measured actual missed care whereas the RN4CAST study measured nurse perceptions of missed care, and peer-reviewed research has shown a disconnect between perception and actual observation (Sale, Beaton, Bogoch, Elliot-Gibson, & Frankel, 2010). Other possible reasons could be that the demonstrator model was created with data from different sources, such as, patient data was taken from a neurological unit; subject matter expert was from medical-surgical unit; unit layout was built from civil engineering manual. Further research is required to examine the large volume of missed care needs to be examined further.

Dabney & Kalisch, (2015) reported that increased nurse-patient ratios were associated with a greater incidence of *missed* care. A similar relation was observed with the demonstrator modelling results of *missed care* as high NPR had greater *missed care* in comparison to lower NPR. Chapman, Rahman, Courtney & Chalmers, (2016) reported that increased *missed care* led to increased overtime which can lead to increased workload for nurses (Alghamdi, 2016; Silas, 2015; McGillis Hall et al., 2005). As illustrated in Figure 5, a small fraction of 'missed care' can also be observed for Low NPR. Even though a NPR of 1:2 may be lower than is realistic in such wards, it shows that there are still missed tasks. This was caused by the arrival of tasks at the end of shift that the simulated nurse was unable to complete before shift-end.

In this model, each room consists of two patient beds; the operational logic is programmed in a way that the simulant-nurse can walk to the nurse station only when all patient bedside priority tasks are completed. For medium NPR level, the simulant-nurse had to walk between two rooms and a nurse station. Since the two rooms are arranged closely to each other, the simulant-nurse walked less. However, for low NPR level since there is just one room and a nurse station, the simulant-nurse walked relatively more (i.e. 4% more). The virtual layout programmed consists of a hypothetical floor layout with scaled drawings of patient rooms and a nurse station. Further research is needed to estimate the impact of floor layout and bed assignment on workload and care quality.

In this research, *task(s) in queue* is treated as a mental workload indicator (Potter et al., 2009), but it also related to care quality. The number of *tasks in queue* has a direct impact on Quality of Care indicators. If the number of tasks *in queue* is substantial, then *task in queue time* and *missed care* will also be greater, as observed in high NPR.

2.7 Implications to Nursing Management

The ability to create a computerized model to simulate nursing care, staffing conditions and related outcomes offers a promising strategy to test the impact of various administrative decisions on a range of nurse and patient outcomes. For instance, the implementation of engineering techniques such as Lean may lead to an increased potential for making mistakes, injuries and missing less urgent care tasks which lead to a drop-in the quality of care (Moraros et al., 2016). This novel nurse focused approach to DES modelling can provide insight to the impact of this new design policy proactively. This framework for this nurse focused DES modelling can be adapted to proactively quantify the impacts of proposed policy changes and technical design decisions. This could be useful for hospital managers, healthcare practitioners, researchers, architects, engineers and policymakers, and provide a more cost-effective and safer alternative to the current trial and error methodologies.

2.8 Methodological Issues for the Demonstrator Model

Like all computer models, the current model will suffer from the "garbage-in garbage-out" (GIGO) phenomenon. The current modelling approach needs to be further developed to test and adjust for possible in-data errors. The current demonstrator model was built on existing 1-month Infor healthcare (GRASP) data from a metropolitan area hospital and from a single inpatient unit. This dataset (GRASP) consisted of only standardized task durations, lacked variability in terms of nurse skill level (novice/expert), and did not reflect patient acuity. If the Infor healthcare (GRASP) dataset failed to capture other nurse activities, then the workload in the model would be an underestimate and the quality of care would likely decline. Further research is needed on the extent to which the Infor healthcare (GRASP) data system captures all relevant nurse activities. This model's adaptability is not contingent on Infor healthcare (GRASP) system; In the absence of such a system, other cost center reporting system or Electronic Health Reporting (EHR) can be used. Other limitations included the use of a single subject matter expert to construct the nurse operating logic in the model, and the use of scaled drawings rather than actual floor plans. Further field validation studies are needed to address these issues. The modelling method itself allows for testing of the potential impacts of different task prioritization strategies.

Future work includes exploring additional indicators for workload and quality of care, such as biomechanical loading and fatigue, testing other unit layouts and design factors such as patient acuity. Using up to 1 year of historical care delivery data (Infor healthcare/GRASP). A field-validation study incorporating nurse experience/competency levels (novice, expert) and using acuity sensitive time duration inputs would be a needed next step in the development of this DES tool. The model needs to be extended, validated and tested for utility to support real-world management and decision making.

2.9 Conclusion

This chapter demonstrated the capability of a novel nurse-focused simulation approach, that simulated the nurse's process of care delivery to help hospital administrators understand, quantify and predict the impact of changing NPRs in terms of nurse workload and care quality. In this simulation, as the number of patients per nurse increased (from Low, Medium, High), nursing workload increased *(*120% increase in *task in queue;* 110% increase in *walking distance)*, and Quality of Care deteriorated *(*120% increase in *missed care;* 20% increase in *task in queue time).*

CHAPTER 3

PILOT MODEL EXTENSION: NURSE-PATIENT RATIO & PATIENT ACUITY

Chapter 2 successfully demonstrated the use of nurse-focused DES modelling by quantifying nurse workload and quality of care. The aim of this chapter was to extend the nurse-focused DES modelling approach developed in Chapter 2, by father developing the model and quantifying the impact of changing patient acuity levels and nurse-patient ratios on nurse workload and quality of care indicators. The emphasis here was on the development of an adaptable content sensitive method, rather than a definitive general answer to a specific scenario of interest to a stakeholder. While there are several drivers of workload, patient acuity and nurse-patient ratio are two of the most important contributors (Aiken et al., 2001; Canadian Institute of Health Information, 2017; Rogers, Buckheit, & Ostendorf, 2013). This chapter further addresses the need of focusing on HCP to improve the healthcare system, outlined in editorial of the recent special issue: 'Ergonomics and Human Factors in Healthcare System Design' in IISE Transactions in Occupational Ergonomics and Human Factors (Neumann et al., 2018). This chapter makes the necessary methodological advancements in this long-term goal.

This chapter addresses RQ 2 – *How do changes in patient acuity and NPR impact indicators of nurse and patient outcomes?*

3.1 Methods

The model was created using a DES environment software Rockwell (ARENA). The model imitates the care delivery process of an inpatient unit of a hospital. The model was created and extended in consultation with a nursing specialist. Figure 6 represents the main inputs and outputs of the model. The main inputs are: 'patient care data', 'operating logic' and 'virtual layout'. In this chapter, the outputs included quality of care and nurse workload. Quality of care is assessed by 'missed care', 'missed care time' and 'care delivery time'. Nurse workload indicators include 'task in queue' and 'cumulative walking distance'. These are explained below:

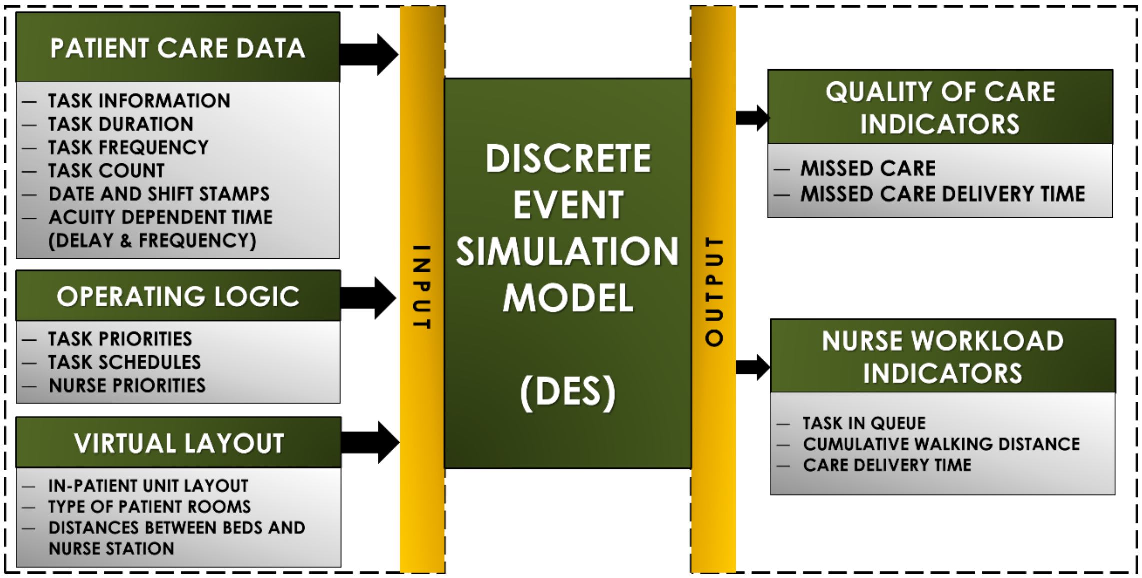

Figure 6 represents the Inputs and Outputs programmed in the extension of the Pilot DES model

3.2 Model Inputs

3.2.1 Patient care data

This input specifies nurse work demands using institutional records of care delivery. Similar to Chapter 2, this dataset was obtained from a neurological in-patient unit for a period of one month from a large urban academic health centre in Ontario, Canada. Patient care data is part of a workload report generated from a management information processing system called Infor healthcare, formerly GRASP (Grace Reynolds Application of the Study of PETO).

GRASP is a workload tracking software that uses standardized time duration with a 7% Personal Fatigue and Delay factor; It is used by approximately 70% of the hospitals in Ontario (Song et al., 2004). In United States, 72% of the hospitals use Infor healthcare (Infor, 2016). Data is recorded by nurses into an Electronics Health Records (EHR) system. The EHR assists decision making (Ben-Assuli, Sagi, Leshno, Ironi, & Ziv, 2015). Patient care data includes the daily care delivery tasks performed by nurses categorized as follows: *Task information* such as task group (e.g. assessment and planning); sub-task within the task group (e.g. Braden scale assessment); time and date.

For this research, *Task frequency* was calculated using an average of task count for an individual task group across all patients per day for a period of one month. The *task duration* for each task group was calculated using a frequency-weighted average of the sub-tasks for each group. The GRASP data was used to create probabilistic time profiles of care tasks in the model. Table 3 represents tasks programmed in the DES model and task duration for the current demonstration model.

3.2.2 Operating Logic

Similar to chapter 2, the operating logic entails the workflow process – task schedules, task priorities, nurse priorities, call tasks and task location. *Task schedule* refers to tasks that follow an established schedule and those that occur randomly throughout the shift. For example: hygiene is scheduled for once a day at 8am. However, the hygiene task can happen at any time (randomly) as well. In the case of random task schedule, for example: bed linens are changed as per schedule but may need to be changed again due to unexpected soiling late in the day. In this modelling example, nutrition, hygiene, admission and discharge are identified as both, scheduled and random tasks. *Task priorities* indicate which tasks have an increased priority for completion over other tasks. In this model, the nurse priorities are programmed to perform the highest priority task first, regardless of distance. There may be occasions where more than one task bears the same priority. In this case, the nurse priority was built such that the nurse simulant performs the task with the least walking distance assigned the highest priority. Within the simulated environment, there are also 'call' tasks that are called directly by the patient at random intervals. A 10% proportion of tasks were programmed as 'call tasks', in consultation with the subject matter expert. In the case of vascular access, for example, if a patient's IV needle becomes displaced, the nurse performs IV maintenance, which is a task that was not scheduled. Instead, this task was called directly from the patient's bedside and is modelled as an event that happens at the patient bedside. The task location was determined for each task - occurring either at the nurses' station or patient bedside. These 'call tasks' had different sensitivity to patient acuity, in terms of task frequency and/or task duration, for each care tasks. Table 3 illustrate the acuity sensitivity, task priority level, task scheduling type and task location of all care tasks programmed in the DES model.

Table 3 illustrate the patient care delivery tasks, programmed in the DES model along with their task distribution type, task delivery location, task duration, task priority level and acuity sensitive tasks

Task Group	Priority (rank)	Task distribution type	Task delivery location	Time Duration (min) [Baseline case]	Acuity Sensitive task?	
					Time Duration	Task Frequency
Medication	1	Random intervals	Patient bedside	6.51	✓	
Vital Signs	2	Random intervals	Patient bedside	5.26	-	✓
Assessment and Planning	3	Random intervals	Patient bedside & Nurse Station	6.93	-	-
Vascular Access	4	Random intervals	Patient bedside	31.50	-	✓
Treatments	5	Random intervals	Patient bedside	9.50	✓	✓
Activity	6	Random intervals	Patient bedside	26.10	✓	✓
Consultation	6	Random intervals	Patient bedside	6.00	-	-
Hygiene	6	Random intervals + Scheduled interval (8:00AM)	Patient bedside	13.32	✓	✓
Nutrition	6	Random intervals & Scheduled intervals (8AM, 12PM, 5PM)	Patient bedside	17.05	-	-
Other Direct Nursing Care	6	Random intervals	Patient bedside	25.65	✓	✓
Admission	6	Scheduled interval (7:30AM)	Patient bedside	32.10	-	-
Discharge	6	Scheduled interval (7:30AM)	Patient bedside	21.40	-	-
Evaluation	6	Random intervals	Patient bedside & Nurse Station	3.00	✓	✓
Non-patient care	6	Random intervals	Patient bedside & Nurses' Station	13.79	-	-
Elimination	7	Random intervals	Patient bedside	19.91	-	-
Teaching and Emotional Support	8	Random intervals	Patient bedside	19.68	✓	✓

3.2.3 Virtual layout

Similar to chapter 2, the virtual layout refers to the physical environment programmed into the model. The layout was built using Microsoft Visio software. The virtual layout drawing reflected the overall floor plan details of the sample inpatient unit including the total number of beds and active beds, the nursing station and bed location, room type (single, double, quad), and the distance between patient beds and the nurses' station. The virtual layout is used for visual verification during simulation conditions i.e. to visualize the nurse's movement and nurse priorities.

We note that each of these elements: patient care data, operating logic and virtual layout, can and should be adapted to specific contexts. The current model demonstrates an adaptable approach to modelling that can be applied to different care system designs**.** The emphasis here was to test the ability to simulate the process of care delivery using flow simulation (DES) under different technical design and operational polices (nurse-patient ratio and patient acuity) by running a model sensitivity analysis. The demonstrator model was created from different sources, such as, patient data was taken from a neurological unit; subject matter expert was from medical-surgical unit; unit layout was built from a hospital layout manual). Using data from different sources, may compromise the quality of modeling outputs.

3.3 Model Outputs

Model outputs include indicators of nurse workload and quality of care. Casner & Gore, (2010) defines workload in three aspects: a) mental activity; b) physical activity and c) time pressure. This study measures *nurse workload* across all three of these aspects through the following indicators: 'task in queue' represents the number of pending tasks for nurses. This is a mental workload indicator that is associated with medical errors (Potter et al., 2009). 'Cumulative walking distance' is the total distance walked by the nurse during a shift in metres. This indicator speaks to the physical activity aspect (Feehan et al., 2018). 'Care delivery time', cumulative time nurse spent while delivering care. This indicator speaks to the time pressure aspect (Kieft, De Brouwer, Francke, & Delnoij, 2014).

Quality of care was quantified using the following indicators: 'missed care' and 'missed care delivery time'. 'Missed care' amounts to the care delivery tasks that were not performed by nurse before the end of shift. 'Missed care' tasks are not essentially 'missed'; According to the model, these are tasks that could not be completed before the end of the shift. In practice, the nurse may have to stay beyond the end of their shift to complete these tasks. In some cases, these tasks may get transferred to the next nurse, thus increasing their workload. 'Missed care delivery time' is an indicator of overtime. It is the time required to perform care tasks left undone before the end of shift.

3.4 Experimental Design and Analysis

In this study, we aimed our experimental conditions to span a broad range of nurse-patient ratios and patient acuity scenarios. *Nurse-patient ratio* refers to the number of patients assigned to one nurse. For this study, different levels of nurse-patient ratios were: 1 nurse assigned to 2, 3, 4, 5, 6, 7 or 8 patients given that the most common nurse-patient ratios in practice are 1:4, 1:5 and 1:6.

Patient acuity is the severity illness of a patient (Brennan, 2011). In this model, patient acuity was operationalized as a function of the frequency and task duration for select care task. These were identified by a subject matter expert – a registered nurse with 25+ years of experience. As illustrated in Table 3, only tasks such as medication, vital signs, evaluation, vascular access, treatments and consultation were classified as acuity sensitive – when acuity level increases so does the task frequency and/or time duration. For this chapter, different levels of patient acuity were explored: present acuity level (baseline case), and -10%, +10%, +20%, +30% of the baseline case. In reality, the '-10% of the baseline case' for patient acuity may not exist as newer policies support earlier discharges and shorter lengths of stay to improve system throughput and thereby increase the overall patient acuity in the unit. Hence, the +10%, +20% and +30% increases in patient acuity levels are more realistic future scenarios given the current policy. This chapter is looking across decades of policy effects over longer times.

3.5 Modelling experiment

The DES model was tested on a combination of different levels of nurse-patient ratios and patient acuity as described above. The model was run on 35 different conditions, each consisting of a combination of different acuity levels and nurse-patient ratios. Each condition was run for 365 days (1 year), calculated using the method of Banks et al., (2005). A warm up time period of 21 days was based on the method recommended by Hoad et al., (2008). A full factorial ANOVA was used to check statistically significant difference between mean values of indicators of nurse workload and quality of care. For Post Hoc analysis, Tukey's test was used to determine where does the significant difference exist. For ANOVA and Post Hoc analysis, the independent variables (IV) were always nurse-patient ratio and patient acuity levels, and the dependent variable (DV) was one indicator of either nurse workload or quality of care. In addition, linear regression models (Aiken, 1991), were tested to determine the strength of relationships between indicators of nurse workload and quality of care with both nurse-patient ratio and patient acuity. A similar configuration of IV and DV was used for regression analysis. These analyses were conducted using IBM SPSS Statistics, Version 24.0.

3.6 Model Verification

This research made use of the model verification techniques outlined by Sargent (2013). *Repeatability and Reproducibility test* – The ability of a model to produce similar results under similar conditions when the model is run of different devices by different operators. *Animation and graphics test* – This test allows the programmer to check if the model is following the operational logic, whilst running simulation. *Degenerate testing* – the degeneracy of a model's behaviour is checked by running the simulation model on conditions that will produce near zero output e.g. if there are no patients on the unit, then the walking distance of the nurse should be zero. *Data relationship correctness* – The ability to identify expected relationships among variables recorded whilst running simulation. For instance, the increase in number of tasks in queue should observe an increase in care delivery time. Lastly, *face validity* – the outputs of the simulation model were shown to a subject matter expert, an RN with 25+ years of experience, as well as to the directors and unit managers of the partner site (n = 12), to see if reasonable outcomes are being produced (Zanda, Zuddas, & Seatzu, 2018).

3.7 Results

A novel approach to nurse focused DES modelling methodology was successfully developed. This adaptable demonstrator model quantified the effects of changing nurse-patient ratios and patient acuity in terms of quality of care and nurse workload.

The effects on indicators of quality of care and nurse workload are described on the next page.

3.7.1 Quality of care indicators

Missed care – As illustrated in Figure 7, a range of 2 to 115 tasks were missed at the end of the shift. In cases with a 1:4 nurse-patient ratios and a normal patient acuity level (baseline), 23 tasks were missed.

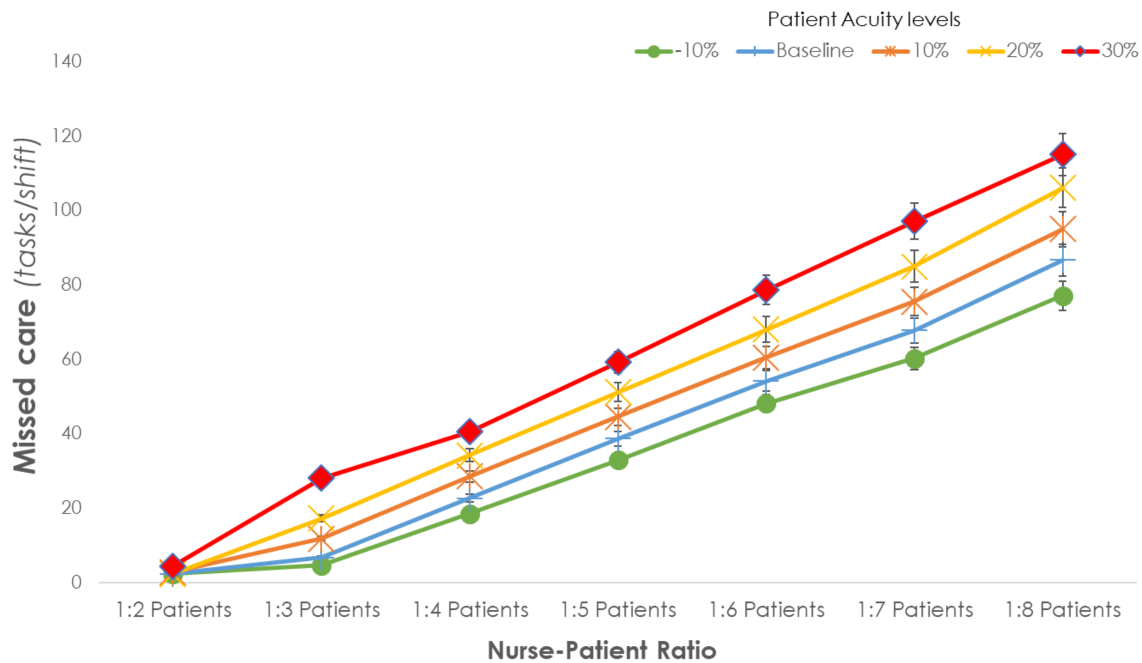

Figure 7 illustrate the average number of Missed care (tasks/shift) per shift. The error bars illustrate the standard deviation for Missed care. The highest no. of care tasks missed is 115 tasks for 30% increase in patient acuity with 1:8 nurse-patient ratio

Missed care delivery time – As illustrated in Figure 8, a range of 1 to 38 hours were spent delivering care for missed tasks.

Detailed results for each condition are illustrated in Table 4.

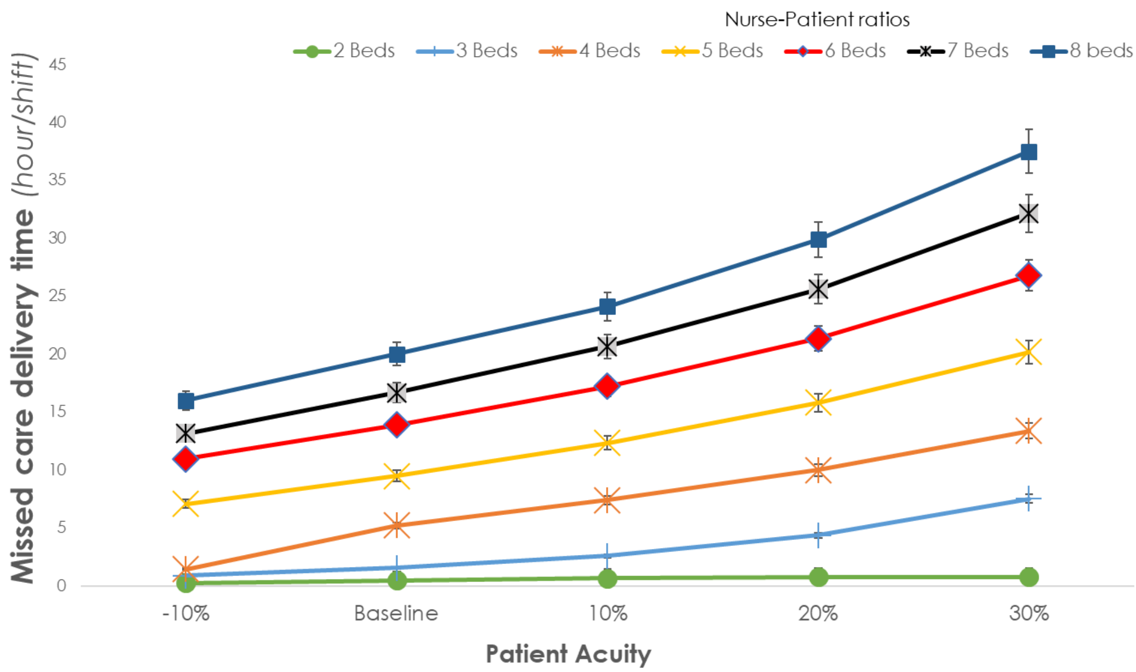

Figure 8 represents Missed care delivery time (hours/shift) per shift. Where, the error bars illustrate the standard deviation

A full factorial analysis *for 'Quality of care' indicators* showed a statistically significant difference ($p<0.05$) for 'missed care time' and 'missed care'. As illustrated in Table 4, Post Hoc tests (Tukey test) for 'Quality of care' indicators, show a statistically significant difference for all cases of 'missed care time' and 'missed care'. Furthermore, the main effect of nurse-patient ratio and patient acuity, were significant on 'missed care' and 'missed care time' ($p<0.05$).

3.7.2 Nurse workload indicators

Care delivery time – As illustrated in Figure 9, a saturation effect can be observed for all conditions of 'care delivery time', with exception of the five conditions bearing nurse-patient ratio 1:2. For the remaining 30 conditions, the nurse-simulant spent ~11.8 hours delivering care out of a 12-hour shift.

Task in queue – As illustrated in Figure 10, a range of 1 to 63 tasks were always in queue to be completed.

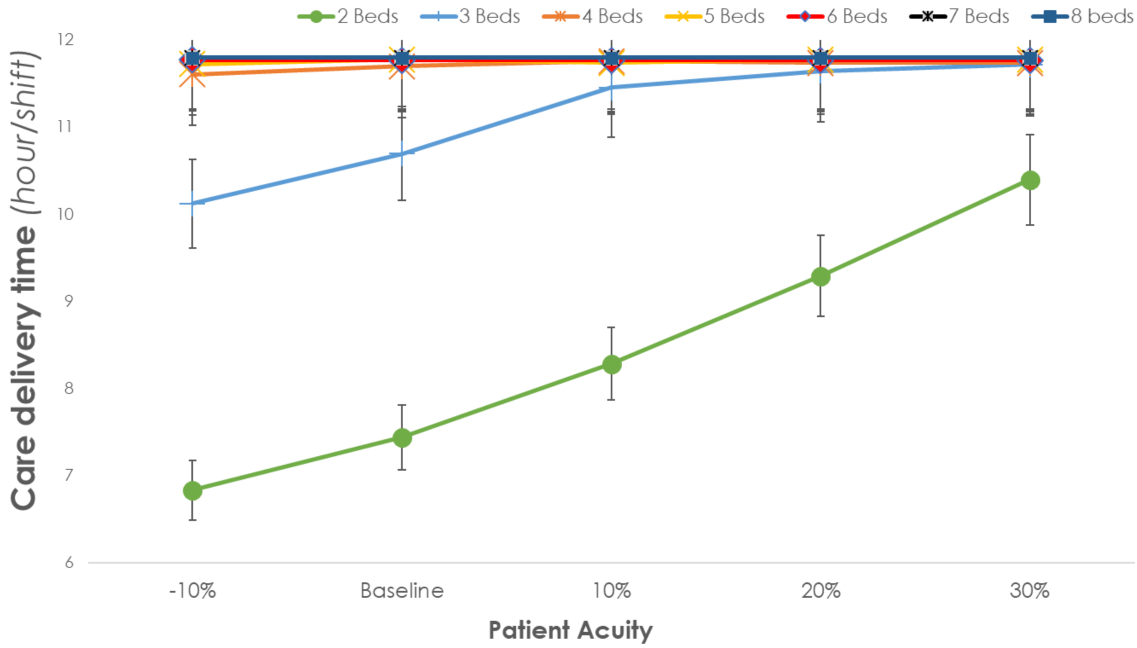

Figure 9 illustrates Care delivery time (hour/shift). Where nurses assigned to 4, 5, 6, 7, 8 beds worked constantly for ~11.8 hours. The error bars illustrate the standard deviation for Care delivery time

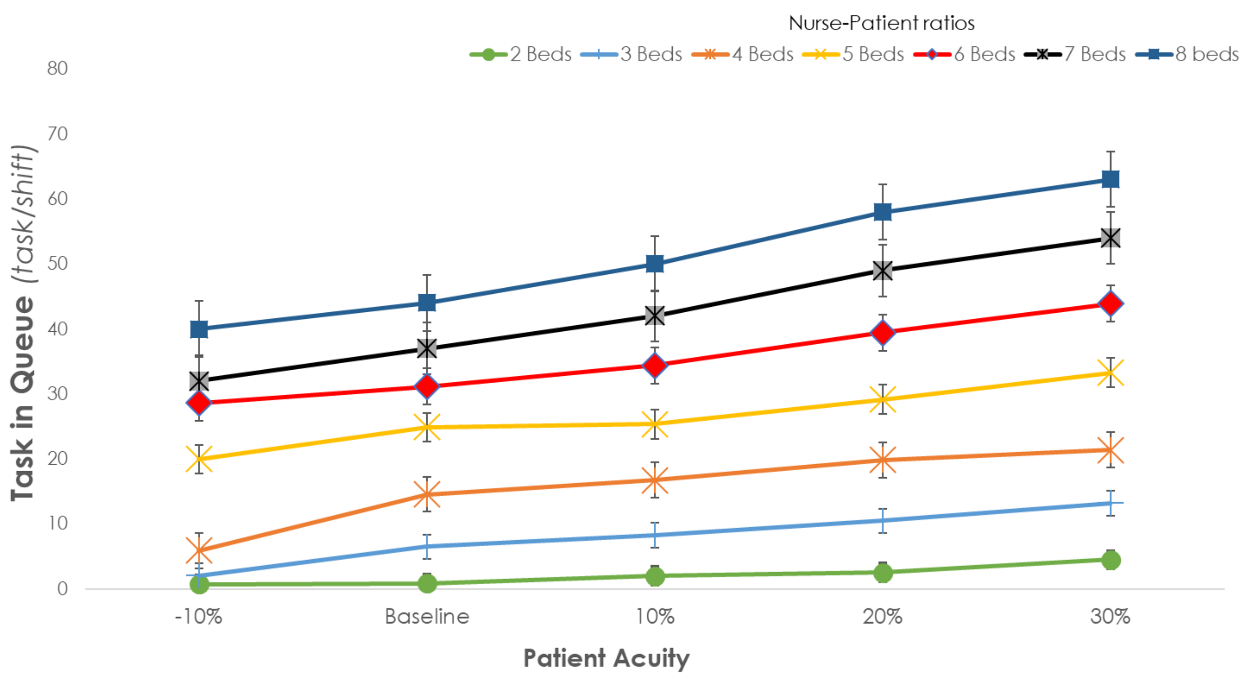

Figure 10 show the effect of varying patient acuity and nurse patient ratio on the average number of Task in queue (tasks/shift) per shift. The error bars illustrate the standard deviation

Cumulative distance walked – With the exception of nurse-patient ratios 1:2, 1:3 and 1:4, it was observed that the nurse walked less when patient's had lower patient acuity level in comparison to high patient acuity level. Detailed results for each condition are illustrated in Table 4.

A full factorial analysis for *'Nurse workload' indicators* showed a statistically significant difference ($p<0.05$) for 'task in queue', 'cumulative care delivery time'. As illustrated in Table 4, Post Hoc tests (Tukey test) for *'Nurse workload' indicators*, show a statistically significant difference for all cases of 'task in queue' with the exception of 'cumulative care delivery time' (in the case of 4 & 5 beds, 4 & 6 beds, 5 & 6 beds, 7 & 8 beds) and 'cumulative walking distance' (only for the case of: 10% & 30% of baseline case, 20% & 30% of the baseline case). Furthermore, the main effect of nurse-patient ratio and patient acuity, were significant on 'cumulative care delivery time', 'cumulative walking distance' and 'task in queue' ($p<0.05$).

The following equations provide an example of how data extracted from these computerized simulation can yield linear regression equations (Aiken, 1991) to predict Quality of care ('missed care', 'missed care time') and Nurse workload indicators ('care delivery time', 'cumulative walking distance', 'task in queue'):

$$Y_{(MISSED\ CARE)} = -84.51 + 15.06\, X_{NPR} + 4.95\, X_{PA} \qquad R^2 = 0.91$$

$$Y_{(MISSED\ CARE\ TIME)} = -35.27 + 4.49\, X_{NPR} + 2.34\, X_{PA} \qquad R^2 = 0.87$$

$$Y_{(CARE\ DELIVERY\ TIME)} = 107.59 + 88.45\, X_{NPR} - 7.26\, X_{PA} \qquad R^2 = 0.84$$

$$Y_{(CUMULATIVE\ WALKING\ DISTANCE)} = 110.66 + 88.49\, X_{NPR} - 7.41\, X_{PA} \qquad R^2 = 0.71$$

$$Y_{(TASK\ IN\ QUEUE)} = -47.17 + 8.52\, X_{NPR} + 2.71\, X_{PA} \qquad R^2 = 0.83$$

where, X_{NPR} represents the independent variable of Nurse-Patient ratio (no. of beds per nurse) and X_{PA} represents the independent variable Patient Acuity (% of the baseline).

*Table 4 show the effect of varying Patient acuity levels & Nurse-patient ratios in terms of 'Quality of care' & 'Nurse workload' indicators. Post Hoc test (Tukey's) concluded statistically significant difference except for 'Care delivery time' i.e. 1:4 & 1:5 beds, represented by * ; 1:4 & 1:6 beds represented by ξ ; 1:5 & 1:6 beds represented by †; 1:7 and 1:8 beds represented by § and 'Cumulative distance walked' i.e. 10% & 30% of baseline represented by Φ ; 20% & 30% of baseline represented by ∂. (Numbers are rounded off to the nearest integer, except for 'care delivery time')*

#	Nurse Patient Ratio	Patient Acuity	**Quality of Care** Indicators		**Nurse Workload** Indicators		
			Missed Care *tasks* (Δ% base)	**Missed Care Time** *hours (Δ% base)*	**Care Delivery Time** *hours (Δ% base)*	**Task in Queue** *tasks (Δ% base)*	**Distance Walked** *meter (Δ% base)*
1		-10%	**2** (-1%)	**0** (-25%)	**6.8** (-8%)	**1** (-11%)	**298** (1%)
2		Baseline	**2** (0%)	**1** (0%)	**7.4** (0%)	**1** (0%)	**296** (0%)
3	1:2	10%	**3** (18%)	**1** (25%)	**8.3** (11%)	**2** (142%)	**264**$^{\Phi}$ (-11%)
4		20%	**2** (-1%)	**1** (47%)	**9.3** (25%)	**3** (204%)	**226**$^{\partial}$ (-24%)
5		30%	**4** (91%)	**1** (128%)	**10.4** (40%)	**5** (439%)	**160**$^{\Phi\partial}$ (-46%)
6		-10%	**5** (-31%)	**1** (-43%)	**10.1** (-5%)	**2** (-68%)	**375** (18%)
7		Baseline	**7** (0%)	**2** (0%)	**10.7** (0%)	**7** (0%)	**318** (0%)
8	1:3	10%	**12** (77%)	**3** (67%)	**11.5** (7%)	**8** (27%)	**280**$^{\Phi}$ (-12%)
9		20%	**17** (160%)	**4** (183%)	**11.6** (9%)	**10** (61%)	**264**$^{\partial}$ (-17%)
10		30%	**28** (323%)	**8** (386%)	**11.7** (10%)	**13** (103%)	**255**$^{\Phi\partial}$ (-20%)
11		-10%	**18** (-19%)	**3** (-33%)	**11.6***§ (-1%)	**6** (-59%)	**298** (7%)
12		Baseline	**23** (0%)	**5** (0%)	**11.7***§ (0%)	**15** (0%)	**279** (0%)
13	1:4	10%	**28** (26%)	**7** (42%)	**11.8***§ (0%)	**17** (15%)	**278**$^{\Phi}$ (-1%)
14		20%	**34** (51%)	**10** (92%)	**11.7***§ (0%)	**20** (36%)	**265**$^{\partial}$ (-5%)
15		30%	**41** (79%)	**13** (157%)	**11.7***§ (0%)	**21** (47%)	**276**$^{\Phi\partial}$ (-1%)
16		-10%	**33** (-15%)	**7** (-25%)	**11.7***† (0%)	**20** (-20%)	**472** (4%)
17		Baseline	**39** (0%)	**9** (0%)	**11.8***† (0%)	**25** (0%)	**452** (0%)
18	1:5	10%	**44** (15%)	**12** (30%)	**11.7***† (0%)	**25** (2%)	**468**$^{\Phi}$ (4%)
19		20%	**51** (32%)	**16** (67%)	**11.8***† (0%)	**29** (17%)	**486**$^{\partial}$ (8%)
20		30%	**59** (53%)	**20** (113%)	**11.8***† (0%)	**33** (34%)	**517**$^{\Phi\partial}$ (14%)
21		-10%	**48** (-11%)	**11** (-21%)	**11.8**§† (0%)	**29** (-8%)	**552** (-3%)
22		Baseline	**54** (0%)	**14** (0%)	**11.8**§† (0%)	**31** (0%)	**571** (0%)
23	1:6	10%	**60** (12%)	**17** (24%)	**11.8**§† (0%)	**34** (10%)	**586**$^{\Phi}$ (3%)
24		20%	**68** (26%)	**21** (54%)	**11.8**§† (0%)	**39** (27%)	**620**$^{\partial}$ (9%)
25		30%	**79** (45%)	**27** (93%)	**11.8**§† (0%)	**44** (41%)	**673**$^{\Phi\partial}$ (18%)

#	Nurse Patient Ratio	Patient Acuity	**Quality of Care** Indicators		**Nurse Workload** Indicators		
			Missed Care *tasks* *(Δ% base)*	**Missed Care Time** *hours (Δ% base)*	**Care Delivery Time** *hours (Δ% base)*	**Task in Queue** *tasks (Δ% base)*	**Distance Walked** *meter (Δ% base)*
26	1:7	-10%	**60** (-11%)	**13** (-21%)	**11.8**§ (0%)	**32** (-16%)	**635** (-3%)
27		Baseline	**68** (0%)	**17** (0%)	**11.8**§ (0%)	**37** (0%)	**657** (0%)
28		10%	**75** (12%)	**21** (24%)	**11.8**§ (0%)	**42** (14%)	**674**$^{\Phi}$ (3%)
29		20%	**85** (26%)	**26** (54%)	**11.8**§ (0%)	**49** (32%)	**713**$^{\partial}$ (9%)
30		30%	**97** (43%)	**32** (93%)	**11.8**§ (0%)	**54** (46%)	**774**$^{\Phi\partial}$ (18%)
31	1:8	-10%	**77** (-11%)	**16** (-10%)	**11.8**§ (0%)	**40** (-9%)	**762** (-3%)
32		Baseline	**87** (0%)	**20** (0%)	**11.8**§ (0%)	**44** (0%)	**788** (0%)
33		10%	**95** (10%)	**24** (21%)	**11.8**§ (0%)	**50** (14%)	**807**$^{\Phi}$ (2%)
34		20%	**106** (22%)	**30** (49%)	**11.8**§ (0%)	**58** (32%)	**859**$^{\partial}$ (9%)
35		30%	**115** (33%)	**38** (88%)	**11.8**§ (0%)	**63** (43%)	**961**$^{\Phi\partial}$ (22%)
Average			**46**	**13**	**11**	**26**	**489**

3.8 Model Verification

Repeatability and Reproducibility test – The DES model was run on 5 different devices. 3 PCs and 2 Mac devices. Rockwell (ARENA) is not supported on Mac therefore, a windows emulator was installed. The DES model produced similar range of results across all devices, where the coefficient of variation was <7% across all indicators of nurse workload and quality of care. Thus, verifying the programming of this model.

Animation and Graphics test – An animation component was built inside the DES model. Whist running simulation, it was observed that the simulant- nurse was following the operational logic programmed into the model. The model was programmed to deliver the most urgent (high priority) care at the closet distance; the DES model was following this logic. Thus, verifying the programming of this model.

Degenerate Testing – The DES model was run with only one patient assigned to a nurse with 90% reduction in task frequency. The care delivery time was reduced to <1 hour. The DES model behaved accordingly thus, verifying the programming of this model.

Data relationship correctness – The simulation model was run on 35 different conditions; all illustrated a simultaneous increase/decrease between of indicators 'missed care' and 'missed care delivery time' model. Thus, verifying the programming of this model.

Face validity – The results of these 35 conditions were shown to a subject matter expert and 12 directors and unit of managers of the partner hospital. They concluded the effect of nurse workload and quality of care produced as the outputs by the DES model was typical to what can be observed in the field.

3.9 Discussion

This chapter provides an adaptable modelling approach that can reveal the quantifiable effects of changing technical design policies on quality of care and nurse workload. In addition to this, the chapter addresses the need for a dynamic tool, recommended by the National Advisory Group on the Safety of Patients in England (2013), that can assess staffing levels (nurse-patient ratio) and patient acuity as a way to address workload and quality of care. As nurse-patient ratio and patient acuity are significant drivers of workload and quality (Aiken et al., 2018; Aiken et al., 2008; Alghamdi, 2016; Hurst, 2018). While traditional simulation approaches have been limited to modelling patients as a 'resource' in the model that flows through the system, stopping at several stations to receive care similar to modelling product flow in a production context. This approach does not provide insight to the impact of operational policy and technical design change in terms of nurse work demands, workload and quality of care. This paper addresses the need of focusing on HCP to improve the healthcare system, outlined in the editorial of the recent special issue: 'Ergonomics and Human Factors in Healthcare System Design' in IISE Transactions in Occupational Ergonomics and Human Factors (Neumann et al., 2018). This HCP focused research was able to quantify the high work demands of nurses, in a work environment with limited autonomy (Kramer & Schmalenberg, 2008; Skår, 2010). Using Karasek's 'Demand Control' model (Karasek, 1979), nursing work can be categorized as high work demand with low autonomy jobs as 'high strain jobs'. Continuous exposures to such high strain jobs can lead to a burnout (Gingras, de Jonge, & Purdy, 2010; Karasek, 1979; Rizo-Baeza et al., 2018). This nurse focussed modeling approach can assist policy makers and healthcare managers to improve the current state nursing by proactively estimating nursing work demands, workload and quality of care under newer polices and technical designs. For instance, the developed modelling capability quantifies how increases in patient acuity, e.g. through earlier release of patients, will increase nurse workload and may compromise care quality. While the effect of the overall proportional increase of nurse-patient ratio and patient acuity on the quality of care and nurse workload was expected, the ability to quantify this effect is unique. A comparison to other published work is presented below.

Quality of care – The range of the nursing care tasks left undone, as quantified by the demonstrator model, (1 to 80 tasks) was consistent with a study on uncompleted nursing care tasks across 12 European countries (Ausserhofer, Zander, Busse, Schubert, De Geest, et al., 2014), with the exception of nurse-patient ratio 1:7 and 1:8. As the study by Ausserhofer et al., (2014) did not account for nurses working with 1:7 and 1:8 nurse-patient ratios. In the case of *missed care delivery time,* an overtime between 7 to 38 hours was recorded, which may not be the case in real-world scenarios where nurses may work faster than the standardized times reported in GRASP systems, in order to keep up. In practice, nurses are under immense time pressures and may be forced to skip low priority tasks that have less impact on the patient such as, some aspects of documentation. If nurses are rushing, however, this may compromise patient safety and quality of care by increasing the prospect of making errors (Recio-saucedo et al., 2018). This nurse focused approach to DES modelling of the care delivery process of nurses can help analyse the impact of changing system design and policy factors in terms of nurse workload and quality of care.

Nurse workload – The demonstrator model shows that the nurse-simulant spent ~11.8 hours delivering care for patients out of a 12-hour shift. Hendrich et al., (2008) conducted a time and motion study at 36 hospitals in 15 states, where they concluded that a nurse spends more than three quarters of their time in delivering nursing care – a result consistent with the findings as reported by the demonstrator model. Besides high physical workload, the model shows nurses to have increased mental workload as well; For *most* conditions, the nurse had a range of 31 to 63 tasks in the *task queue* throughout the shift. These "stacked" tasks lead to increased mental workload (Potter et al., 2009). Nurse walking distance is contingent upon patient assignment and layout (Hendrich et al., 2008). In this study, the *cumulative walking distances for nurses* decreased as the nurse-patient ratio and patient acuity increased, with the exception of nurse patient ratios 1:5, 1:6, 1:7 and 1:8. This study uses scaled drawings of a hypothetical floor plan with an optimistic bed assignment where all patients assigned are in beds next to each other. Due to this optimistic bed assignment, the nurse spent more time delivering care from patient room to patient room instead of going back to the nurse-station. When the nurse was assigned to more than 5 beds, a similar phenomenon was observed but now the nurse was assigned to more beds that meant the distance between the rooms increased and as a result the cumulative walking distance increased by up to 22%. In real-life, the bed assignment is contingent upon various factors such as the treatment priority, nurse skillset, acuity level, bed availability and resource allocation (Schmidt et al., 2013). Therefore, bed assignment is not always optimal. Further research is needed in this area. This computerized simulation approach can be used to study the effects of changing model parameters, such as architectural design of units or impacts of bed assignment strategies; investigations that remain future research tasks.

Regression modelling – The presented equations illustrate an example how data from computerized simulation can be used to generate linear regression equations that may give access to model responses without the need for further modelling expertise. The current examples should be used with caution and adapted to a particular setting before application. Such equations can be used for future system dynamics modelling work, similar to the work of Farid (2017).

3.10 Methodological Modelling Issues for the Demonstrator Model

The demonstrator model is not universal. Model settings span a range of operational conditions which may need to be adapted to a particular setting. While the internal validity checks were positive, an external field validation of the modelling approach is required. The ability to model the process of care delivery in nursing and test different system design and policies offers a proactive assessment tool of possible use to healthcare managers, ergonomists, architects, engineers and researchers. This–approach to nurse-focused DES modelling can be used to understand and quantify the effect of acuity based nurse staffing to utilize available registered nurses (RN) during current nurse shortage, an issue raised by Daly et al. (2009). Furthermore, the approach to modelling the process of care delivery using a nurse focused approach, can be used to develop models in other care scenarios, for instance, home-care or long-term care settings. This simulation modelling approach can also be adapted to test the impact of other drivers of nurse workload.

The simulation model is stochastic in nature, rather than deterministic. Where, the sequence of care tasks generated by the model is different for each patient. Model variability is expressed in terms of standard deviation represented by error bars in Figures 2 to 5. The model was built using existing patient care data (GRASP) from a single inpatient unit. The patient care data (GRASP) was taken for an 'average' month. There may be day-day or patient-patient variability that could be included in the model if that issue was to be examined more closely. In addition, GRASP contains standardized time duration. Therefore, the model lacked information on the time difference between a novice and an expert worker. The inclusion of day-day and patient-patient variability and a non-standardized time duration may affect delivery time as well both within the model and between nurses – a possible extension to the modelling capability in the future.

Simulation and modelling capability developed in these studies requires statistical testing. This creates a dilemma for simulation scientists as statistical difference can easily be rendered significant by running more replications of the model (Neumann & Medbo, 2009). This effect was observed here. Ultimately, it is up to the model user and knowledge user to quantify how big a difference is 'managerially' significant with respect to cost-benefit in the context of using simulation and modelling methodologies.

The Infor healthcare (GRASP) data was taken from a neurological in-patient unit for a period of one month (Fall/September). In an interview with the unit manager, we were advised that nursing workload fluctuates across the seasons of the year, for instance workload increases in the summer due to more cases of head trauma from motorcycle accidents. In this example simulation study, the data was taken during a period of 'mild' workload. Data from other periods could also be used.

Other limitations include consulting only one experienced subject matter expert to set acuity sensitive tasks and construct operational logic, which can be enhanced and validated by engaging the unit nurses directly. This approach to computerized simulation can be used to test different system design and operational policies by quantifying their effect in terms of nurse workload and quality of care. This provides a decision support system for healthcare management and policy makers. Future work includes exploring additional physical indicators of workload (Casner & Gore, 2010): biomechanical load related to injury risks, fatigue aspects relating to medical errors, newer design factors such as location of bed assignments, nurse experience/competency levels (e.g. novice vs expert), day-day and patient to patient variability, and a more substantial validity check (field validation). While the internal verification checks were successful, this demonstrator model needs to be extended and externally validated for real world management and decision making. Further testing is required. Incorporating a healthcare professional focused approach to computerized simulation can influence safety (Carayon, Xie, & Kianfar, 2014), quality and efficiency in daily operations (Norris, 2012; Russ et al., 2013). The ability to model nursing care delivery, patient acuity levels and staffing conditions offers a promising strategy to test and quantify the impact of various operational polices on a range of patient and nurse outcomes. The current model poses an early stage example of an evidence driven "analysis engine" that can provide decision support for those determining the physical and operational parameters in healthcare systems.

3.11 Implications for Healthcare System Engineering

This adaptable modelling approach offers a promising strategy to test the impact of various system design and operational decisions on a range of nurse and patient outcomes. This tool offers a more cost effective and safer alternative to current trial and error methodologies. When human factors and ergonomics are not considered in the design of healthcare management system, more problems tend to occur (Neumann et al., 2018). This novel HCP focused modelling poses as a potential tool to support prospective ergonomics (Robert & Brangier, 2012), to cater to the needs of: *policy makers*, to test consequences of technical design and policy trade-offs; assist *architects*, to better design in-patient unit layout; *hospital managers*, in their daily operational planning; creating safer work environments for *healthcare practitioners* (such as nurses) by quantifying workload demands proactively. Using this nurse-focused DES modelling approach can assist the above-mentioned knowledge users to gain proactive insight to implementing newer technical design and operational decisions. This proactive insight can lead to better technical designs and operational decisions, that may reduce workload that may lead reduced injury rates, reduced absenteeism and decreased errors. However, further testing of this DES modelling approach is needed to affirm this. While the initial results are promising and compare favourably to peer-reviewed published research, this approach should now be tested with these potential users to understand how best to build and apply such models to support their decision-making efforts.

3.12 Conclusion

A novel approach to nurse focused DES modelling capability was created and tested. The demonstrator model successfully quantified the effects of changing nurse-patient ratio and patient acuity in terms of quality of care and nurse workload indicators. As number of patients per nurse and patient-acuity increased so did nurse workload, with an associated decline in care quality. In comparison to the base-case: *missed care* increased up to 323%; *missed care delivery time* up to 386%; *care delivery time* up to 40%, and cumulative *walking distance* up to 22%; and *task in queue up to* 439% in the most demanding scenario tested. The proposed modelling approach offers a cost effective, proactive and safe alternative to the current trial and error methodologies. Computerized modelling can be used to improve quality and inform technical design and operational policy decisions. These simulation models are potential engines for decision support tools for hospital managers and healthcare system decision makers (Schlessinger & Eddy, 2002). Further development and testing of the modelling approach presented here is required. With the demonstrated modelling approach working, it's time to extend the DES modeling capability by improving and testing the accuracy of the model by adapting the model to a real-life unit for field validation.

CHAPTER 4

MODEL VALIDATION

Chapter 2 and 3 demonstrated the successful creation and pilot testing of the novel nurse-focused approach to DES modeling. While the initial results are promising and compare favourably to peer-reviewed published research, this DES modelling capability needs to be externally validated for real world management and decision making. The aim of this chapter is to develop an approach to creating valid nurse-focused simulation model that quantifies quality of care and nurse workload. Developing a validated simulation model opens the door to quantify indicators of quality of care and nurse workload, accurately. Thereby, improving quality and safety for both patients and nurses.

This chapter addresses RQ 3 – *How can this nurse focused DES tool for in-patient care unit be validated?*

4.1 Validating computerized simulation models

Validation is the process of determining the truthfulness of a model (Sterman, 2002). Model validation studies check the accuracy of a model that lies within an acceptable range of accuracy, consistent with the intended application of the model (Sargent, 2013). It is impossible to create a model depicting 100% real-world behaviour (Sterman, 2002). Despite these limitations, organization and policy makers rely heavily on such models (Werth, 2014). Validated models are more credible and more desirable for the knowledge users and stakeholders as they provide more confidence in the data being used to support decision making. Most simulation scholars have recognized the impossibility of completely validating simulation models as no model is perfect (Oreskes, Shrader-Frechette, & Belitz, 1994; Sterman, 1994). Therefore, simulation scholars have suggested tests that can be used to establish the accuracy of the model. These are divided into three domains. First, *in-data validity checks* – simulation models often suffer from the 'GIGO' (Garbage in, Garbage out') phenomena (Kilkenny & Robinson, 2018). The higher the quality of in-data used, the better the output that can be expected. Getting good quality existing input data for the model can be costly and time consuming. It is still a necessary step in model validity (Sargent, 2013). Second, *internal validation check* – models are the 'best' representations of real-world scenarios built on underlying assumptions (Banks et al., 2005). Internal validation checks the internal creation of the logic and structure of the model by checking if the model is behaving as it is supposed or if the model is generating outputs by a mere coincidence. Different types of checks include: 'repeatability and reproducibility' checks the ability to reproduce the same result under the same operating conditions from different devices and analysts; 'extreme condition' where the model is run on extreme unrealistic conditions to see if expected outputs can be produced; and 'output correction' checks if two expected correlated model outcomes are correlating with each other, for example distance walked and walking time. Internal validation checks are further defined in Section 2.3. Third, *the external validation check* refers to the process of comparing the modelling outputs to the data obtained from the field to determine if the model is depicting behavior of a real-world system (Sargent, 2013). This type of validation is expensive, time consuming and in some case require extensive approvals from the organization but is one of the most reliable sources for model validation. While standalone validation checks have existed for several years, creating a validation approach for nurse-focused acute care delivery model has been lacking. This research reports on all three forms of validation checks for a nurse-centred acute care delivery model.

4.2 Methods

4.2.1 Model Creation

The DES model was created using ARENA (Rockwell) software, a Discrete Event Simulation (DES) modelling tool. Inputs to the DES model included indicators from healthcare system design and policies, such as *'Historical patient care data', a* dataset containing information pertaining to the duration and frequency of patient care tasks delivered by the nurses to all patients for a period of one year. The *'inpatient unit layout'* refers to the physical layout of the patient care unit including the location of all patient beds, the nurse station, clean utility and soiled utility rooms, kitchen, linen closet etc. *'Nurse walking patterns'* were defined as the walking sequence of a nurse while performing each specific patient care task. For instance, the care task IV insertion, the movement of the nurse starts from the present location (nursing station) to the medication room, to the *clean* utility room and finally to the patient room. 'Model operating logic' consists of 'task priority rank sequence' and 'nurse care delivery logic'. *'Task priority rank sequence'* refers to the priority rank based on how important some care tasks are in comparison to others. *'Nurse care delivery logic'* is the logic that is programmed into the model that allows the simulant-nurse to decide which care task to perform when tasks have equal priority.

Modeling outputs include indicators for quality of care and nurse workload.

Quality of care indicators included *'Care task waiting time'* that refers to the amount of time a task spends "waiting" before the nurse initiates the task. *'Total missed care'*, represents the number of care tasks that were not completed before the end of the shift. '*Percentage division of missed care'* represents the percent of the care task that were not delivered before the end of shift. For example: For one shift, 65% of the missed care tasks were non-patient care tasks, 33% were teaching and emotional support tasks and 2% were medication tasks etc. This percentage division is transformed into a ranked descending order. 'Missed care delivery time' represents the amount of time it takes to perform these missed care tasks. In most conditions, the present nurse has to stay after the end of the shift to complete these tasks.

Indicators for nurse workload include '*task in queue'* which is a mental workload indicator that pertains to the 'stack' of tasks that a simulant-nurse must perform at any given time of the shift (Potter et al., 2005, 2009). *'Distance walked by simulant-nurse'* refers to the cumulative distance walked by the simulant-nurse during a 12-hour shift. *'Simulant-nurse movements'* is the total number of one-way trips, either direct and indirect, made to patient rooms, clean and dirty utility rooms, kitchen, shower rooms, medication rooms and linen closet. *'Direct Care time'* is the total time a simulant-nurse spends on care task delivery. Direct care time includes a small portion of the walking time i.e. walking that happens inside the patient room.

Figure 11 provides an overview of how the inputs (healthcare system design and policies) and outputs (nurse workload and quality of care) of the DES model are validated by a series of validity checks.

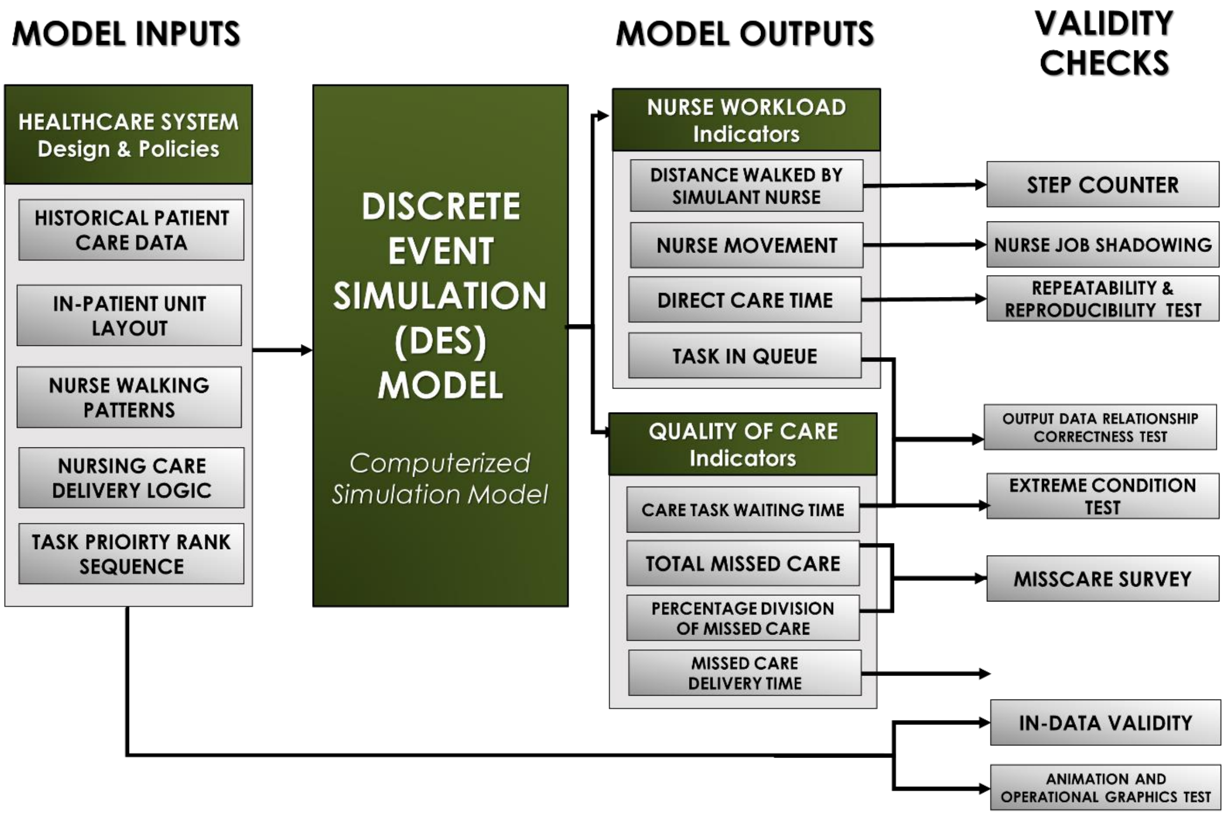

Figure 11 illustrates how the inputs (healthcare system design and policies) and outputs (nurse workload and quality of care) of the DES model are validated by a series of validity checks

'Inpatient unit layout' – The physical dimensions of the selected medical-surgical unit were measured using Bosch Laser Measure (GLM30 100 Ft.). The virtual layout of the unit was developed from these measurements using Microsoft Visio software.

'Nurse walking patterns' – The walking patterns associated with the typical nursing care tasks were developed in consultation with the expert nurses that had over 10 years work experience on the specified unit.

'Nurse care delivery logic' and *'Task priority rank sequence'* represent the operational logic of the model. These were formulated based on the experiences of nurses by means of focus group sessions. Since nurses work more than 12 hours a day, they do not have time to participate in focus group sessions outside of their work hours. Therefore, two focus group sessions were conducted so that half of the nurses can participate in the focus group session while the other half may be present in the unit to deliver timely care to patients. Two focus group sessions were

conducted with a total of 18 RNs from the selected medical-surgical unit. The inclusion criteria were that they must be fluent in English and an RN/RPN with 2 years of experience in medical-surgical unit. The honor system was used to maintain the inclusion criteria for the participants. The focus group sessions identified the care delivery priority sequence and care delivery logic for various nursing care tasks. Participants had 2 to 23 years of experience in the medical-surgical unit with either a bachelor's or master's degree in nursing. The two focus group sessions revealed the following information: For 'nursing care delivery logic', nurses in both sessions unanimously agreed that they would perform the highest care priority task at the shortest distance. For the 'task priority rank sequence', a consensus approach was used in each of the focus group sessions to identify the priority rank sequence for the nursing care tasks as illustrated in Table 5. The two sessions revealed two slightly different task priority rank sequences. Both of these task priority rank sequences were implemented and tested in this chapter.

Table 5 illustrates the task priority rank generated from both focus groups. Where, Highest Priority = 1; Lowest Priority = 16. Task group names were taken from GRASP

Task Group	**Task Priority Rank Sequence for Focus Group 1** *(n = 8)*	**Task Priority Rank Sequence for Focus Group 2** *(n = 7)*
Assessment and Planning	1	1
Consultation	6	7
Elimination	6	3
Evaluation	7	10
Hygiene	6	9
Medication	3	2
Non-patient care	9	12
Nutrition	5	3
Other direct Nursing care	8	8
Teaching & Emotional Support	7	2
Treatments	5	4
Vascular Access	4	5
Vital Signs	1	1
Admission	2	1
Discharge	7	11
Activity	4	6

In addition to in-data validity, the DES model was validated in two phases: internal validation of the model and external validation using field data.

4.2.2 Internal Validation of the Model

This chapter makes use of the following internal validation techniques.

Repeatability and Reproducibility test – To check the variability in the outputs, the simulation model was run multiple times on different devices by two researchers under the same modelling conditions, (Sargent, 2013). The DES model was run 16 times using the same conditions (nurse-patient ratio 1:5, run-length = 365 shifts) on different devices. The DES model was tested on 2 PCs and 2 Macs. Although Rockwell (ARENA) does not support Mac, a Windows emulator package was used.

Output data relationship correctness – This validation technique explores the relationships that are expected to occur within the outputs produced. For instance, 'task in queue' and 'care task waiting time' have a direct proportional relationship (Potter et al., 2005, 2009). If there is a greater 'stack' of tasks to be performed by the nurse, the 'care task wait time' also increases because it would take more time for the nurse to attend to each task. For this validation check, the authors explored the expected relationships between 'task in queue' and 'care task waiting time'.

Extreme Condition Testing – The simulation model is run under extreme conditions to check if the model's behaviour follows the same pattern. For this validation check, the authors ran the DES model on extreme conditions of nurse patient ratios 1:2 and 1:9 to see if the model behaviour changes accordingly, where the base case was set at 1:5. For the case of 1:2, it is expected that the 'care task wait time' should decreases and for the case of 1:9, the 'care task wait time' is expected to increase.

Animation and Operational Graphics – The operational behaviour of the simulation model is observed graphically as the simulation model runs through time. The DES model depicts a 2D diagram of the inpatient unit while running the simulation. The 2D diagram has animations that show the simulant-nurse walking from nurse station to patient beds and other rooms. In addition to this, there is a 'task in queue' counter beside each patient bed. The animation allowed visual inspection of the DES model showing the simulant-nurse was following the nursing care delivery logic and task priority rank levels. The DES model provided bar charts of all indicators of nurse workload and quality of care whilst running the simulation. This provided a quick visual of the validity for the creation and smooth running of the model (Sargent, 2013).This was used to verify if the simulant-nurse was following nursing care delivery logic.

4.2.3 External Model Validation using Field Data

This chapter makes use of the following external validation techniques.

Step counter test – Ten RNs were recruited. The participants were asked to wear a Fitbit™ (Alta Tracker) for an entire 12-hour shift. Two males and eight females participated in this study. Their height ranged from 4′9′′ to 6′5′′. This study yielded 'total distance walked'. These outcomes were compared to modelling output – 'cumulative distance walked by simulant-nurse'. To create consistency, the simulant-nurse was assigned to the same location patient bed assignment as each participant during the step counter study. In addition to this, both task priority rank sequences were tested (as noted in Table 5). Fitbit™ Alta provides accurate measures of steps in adults in comparison to distance walked (Feehan et al., 2018), therefore, the distances reported here are conversions of the number of steps walked by the nurse using Zhang et al., (2018). An intraclass correlation coefficient (ICC) test (Bartko, 1966) was calculated using SPSS Version 20.0, to estimate the similarity between the cumulative distance walked by simulant-nurse' and 'total distance walked', collected using Fitbit™ .

Nurse Job Shadowing – Sargent (2013) describes this as an 'event validation study'. It is the process of comparing the number of events generated during the simulation with actual events where an event entails the number of direct or indirect one-way trips made by the simulant-nurse to certain rooms e.g. the medication room. The 'simulant-nurse's movement' was validated by means of a 'nurse job shadowing' study. Ten RNs were asked to perform their daily care delivery tasks while a researcher shadowed them to observe their movement patterns. Job shadowing was done in time slots of 4 hours between morning (7am to 11am), afternoon (11am to 3pm) and evening (3pm to 7pm). The researcher followed the participants from a distance in an effort to prevent any disturbance and to allow the nurse to work under normal conditions. While shadowing the nurse, the researcher used CAPTIV (Groupe TEA Ergo) to record all trips made by the nurse across various rooms of the unit. Using this dataset, the total number of one-way trips, either direct and indirect, to different rooms of the unit was extracted, such as clean and soiled utility room, medication room etc. These outcomes, referred to as 'nurse movement', were compared to the modelling output – 'simulant-nurse's movement', that also comprised of number of one-way trips made by the simulant-nurse to the clean and soiled utility room, medication room etc. An intraclass correlation coefficient (ICC) test (Bartko, 1966) was calculated using SPSS Version 20.0, to estimate the similarity between the 'simulant-nurse's movement' and 'nurse's movement' and the data collected from the 'nurse job shadowing study' (nurse's movement).

MISSCARE Survey Tool – Registered Nurses (RNs) with a minimum of 6 months' work experience on the medical-surgical unit were invited to participate in this survey either online or hardcopy. The survey consisted of a modified version of the MISSCARE survey tool (Dabney & Kalisch, 2015; Kalisch & Williams, 2009; Winsett, Rottet, Schmitt, Wathen, & Wilson, 2016). The only modification was exclusion of the section 'reasons for missed care', as this was not of interest for this study. The MISSCARE Survey was used to quantify the Nurse's perception of: 1) Total Missed care tasks; 2) Percentage division of Missed care tasks; 3) Missed care delivery time. These were calculated using:

$$MC_{TG} = (SS_A \times R_A) + (SS_F \times R_F) + (SS_{OC} \times R_{OC}) + (SS_R \times R_R) + (S_N \times R_N)$$

$$\% \, DMC_{TG} = \frac{MC_{TG}}{T_{TOTAL}} \times 100$$

$$MC_{TIME} = (\% \, DMC_{TG1} \times G_{TG1}) + (\% \, DMC_{TG2} \times G_{TG2}) + \ldots + (\% \, DMC_{TGn} \times G_{TGn})$$

Where,

MC_{TG} = Nurse's perception of Missed care tasks for a specific Task group

$\% \, DMC_{TG}$ = Nurse's perception of the Percentage division of Missed care tasks

MC_{TIME} = Nurse's perception of Missed care delivery time

TG = Task group (such as: Medication, Vital signs etc.)

T_{TOTAL} = Nurse's perception of total Missed Care tasks

SS = Survey Score

G_{TGn} = Standardized task duration of GRASP Task group *n* R = Rating

A = Always missed R_A = 1

F	=	Frequently missed	R_F = 0.6
OC	=	Occasionally missed	R_{OC} = 0.1
R	=	Rarely missed	R_R = 0.05
N	=	Never missed	R_N = 0

'*Nurse's perception of total missed care tasks'* was compared to the modelling output 'total missed care'. An intraclass correlation coefficient (ICC) test (Bartko, 1966) was calculated using SPSS Version 20.0, to estimate the similarity between the 'missed care' (DES modelling output) and the data collected from the 'nurse's perception of missed care tasks' (MISSCARE survey). *'Nurse's perception of the percentage division of missed care tasks'* were transformed into a descending ranked order. These were compared to the rank order of the DES model indicator: 'percentage division of missed care' task. Spearman Rank Correlation (Blecic, 1999; McDonald, 2014) was calculated using SPSS Version 20.0, to test the correlation of the rank order between 'percentage division of missed care' following task priority rank sequence 1 and 2, and 'the ranked order of nurse's perception of the percentage division missed care task'. *'Nurse's perception of Missed care delivery time'* was compared to DES model output indicator 'missed care delivery time'. An ICC test (Bartko, 1966) was calculated using SPSS Version 20.0, to estimate the similarity between the 'missed care delivery time' (DES modelling output) and the data collected from the 'nurse's perception of missed care delivery time' (MISSCARE survey).

These indicators of missed care were difficult to validate due to nature of how the original survey was designed. MISSCARE is a validated survey but it was not in the same granularity as the model. The survey recorded perception of missed care at the 'care task' level while, the DES model records missed care at the 'task group level'. Therefore, conversions were required where 'care tasks' were converted to 'care task groups' after the surveys were recorded. These were done in consultation with a subject matter expert (SME), an RN with 25+years of experience. In addition, the ratings for each category (always missed, never missed etc.) were formulated in consultation with the SME as well.

4.2.4 Modelling Conditions

The DES model was adapted to represent daytime shifts of a medical-surgical unit where the nurse-patient ratio was set at 1:5 which is a common standard for these types of patient care units

(Aiken et al., 2001). For each external validation check, the same nurse-patient ratio and location-based patient-bed assignment was used to match the operational conditions for each participant (nurse). The model was run for 365 shifts for each condition. These were calculated using the method of Banks et al. (2005) where each shift consisted of 12 hours. To reach an optimal modelling state, a model 'warm up' time of 62 shifts was calculated using the method of Hoad et al. (2008).

4.3 Results

The results are divided into three sections. 1) modelling results, 2) internal validation of the model, and 3) external validation of the model (field study).

4.3.1 Modeling Results

Nurse workload indicators – A range of 7.6 to 11.1 km of 'distance walked by simulant-nurse' was observed for all conditions. 'Simulant-nurse movement' spanned a range of 76 to 88 one-way trips where a 'direct care time' of 10 to 10.8 hr was observed for all conditions. In addition to this, a range of 11 to 18 'task in queue' were observed throughout the shift.

Detailed results are illustrated in Table 6.

Table 6 provides a summary of the modelling outcomes as reported by the DES model

Indicator type	DES output variables	Units	Task Priority Rank Sequence 1	Task Priority Rank Sequence 2
			Mean (SD)	*Mean (SD)*
Nurse workload indicators	Distance walked by Simulant-nurse	km	9 (1.3)	9.2 (1.4)
	Simulant-nurse movement	trips	81 (2.5)	84 (4.3)
	Direct Care time	hr	10.4 (0.2)	10.5 (0.3)
	Task in Queue	tasks	12 (1.1)	15 (2.8)
Quality of care indicators	Care task waiting time	hr	0.9 (0.1)	1.0 (0.2)
	Total missed care	tasks	25.1 (1.2)	25.7 (3.2)
	Percentage division of missed care	highest	non-patient care (23%)	non-patient care (20%)
		lowest	consultation (0%), admission (0%)	consultation (0%), admission (0%)
	Missed care delivery time	hr	2.3 (0.8)	2.5 (1.5)

Quality of care indicators – A 'care task waiting time' of 0.8 to 1.2 hr was observed along with a range of 22 to 31 'total missed care' tasks. The highest percentage division of missed care was for non-patient care tasks (20 to 23%). Non-patient care tasks mainly comprise of documentation tasks. Lowest percentage was tied between consultation (0%) and admission tasks (0%). The 'Missed care delivery time' spanned a range of 1.8 to 2.6 hours. Detailed results are illustrated in Table 6.

4.3.2 Internal Validation of the Model

Repeatability and Reproducibility – The DES model was run a total of 16 times on 2PCs and 2 Macs. They all depicted <1% difference from the base case on 'care delivery time'. This provided supportive evidence that the model can repeat and reproduce similar results.

Output Data Relationship Correctness – Potter et al. (2005, 2009) reported a direct proportional relationship between 'task in queue' and 'care task waiting time'. Using the two 'care task priority sequences' developed in the focus groups, the 'task in queue' of the simulant-nurse increased by 2.1% (11 to 14 tasks), the 'care task waiting time' also increased by 2% (0.8 to 1 hour). Hence the DES model outputs depicted the expected relationships between these two variables.

Extreme Condition Testing – The DES model was run on nurse-patient ratios of 1:2 and 1:9 where the 'task in queue' was 6 and 45 tasks respectively, in comparison to the base case with a nurse-patient ratio of 1:5 where the 'task in queue' was 14 tasks. The DES model was able to produce expected changes in 'task in queue' under these extreme conditions. Thus, passing the extreme condition test.

Animation and Operational Graphics – This test revealed that DES model was following the 'nurse care delivery logic' programmed in the DES model, which is to deliver the highest priority task at the shortest distance.

4.3.3 External Validation of the model – Field Study

Step Counter test – Figure 12 illustrates 'distance walked by the simulant-nurse' and the actual 'distance walked by nurse' (measured using Fitbit™). Both task priority rank sequences produced in the focus groups were tested. The simulated nurse walked an average of 9.1 km (SD = 1.3; Range = 7.2 to 11.1 km) which is equivalent to 11983 steps (SD = 1788; Range = 9448 to 14566 steps) for each task priority rank sequence identified in each focus group. While the actual nurses walked 8.6 km (SD = 1.38; Range = 6.8 to 10.7 km) which is equivalent to 11220 steps (SD = 1823; Range = 8923 to 14042 steps) in a shift, measured using Fitbit™. Relative differences of 1% to 7%, and 4% to 11% were observed when following task priority rank sequences 1 and 2 respectively. An overall ICC of 0.97 was observed between simulation and real-world outcomes. Detailed ICC results are presented in Table 7.

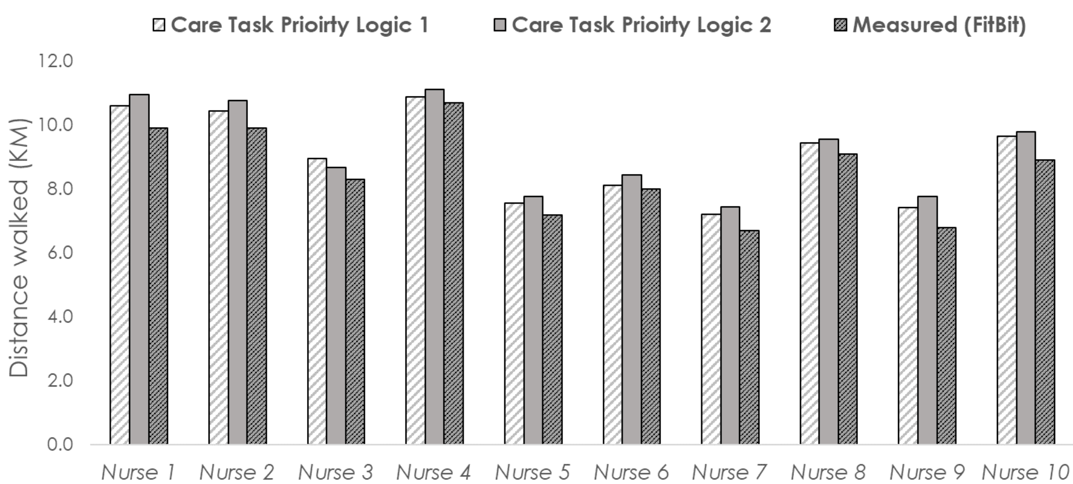

Figure 12 illustrates the 'Distance walked by Simulated-Nurse' (following Task priority rank sequence1 and 2, and the nurse's bed assignment for that shift), and 'Distance walked by Nurse' (measured using Fitbit™)

Table 7 illustrates the Rank order and Percentage divisions for Missed care for Simulant-nurse (Task Priority Rank Sequence for Focus Group 1 and 2) and Actual nurse (Perceptions of Missed Care – MISSCARE Survey)

Study Name	Simulation Output variable	Real-world variable	Task Priority Rank Sequence	Actual Nurse
Step Counter Test	Distance walked by Simulant-Nurse	Distance walked by Actual-Nurse	1	*ICC* = 0.96
			2	*ICC* = 0.92
			Overall	*ICC* = 0.97
Nurse Job Shadowing	Simulant-Nurse movement	Nurse-Movement	1	*ICC* = 0.96
			2	*ICC* = 0.93
			Overall	*ICC* = 0.99
MISSCARE Survey	Missed Care	Nurse's perception of Missed care tasks	1	*ICC* = 0.84
			2	*ICC* = 0.82
			Overall	*ICC* = 0.87
	Missed Care Delivery Time	Nurse's perception of Missed Care Delivery Time	1	*ICC* = 0.77
			2	*ICC* = 0.79
			Overall	*ICC* = 0.85
	Percentage Division of Missed Care tasks*	Nurse's perception of Division of Missed Care tasks*	1	*Spearman Rank Score* = 0.71
			2	*Spearman Rank Score* = 0.65
			Overall	*Spearman Rank Score* = 0.78

Nurse Job Shadowing – The highest number of one-way trips (both direct and indirect) were made to 'patient rooms', followed by 'nurse station' and 'medication room'. The nurse job shadowing data was found to be consistent with the DES model following task priority rank sequence1 and 2. Detailed results are represented in Figure 13. A relative difference of 5.5% to 11% and 4% to 16% were observed when following task priority rank sequence 1 and 2, respectively.

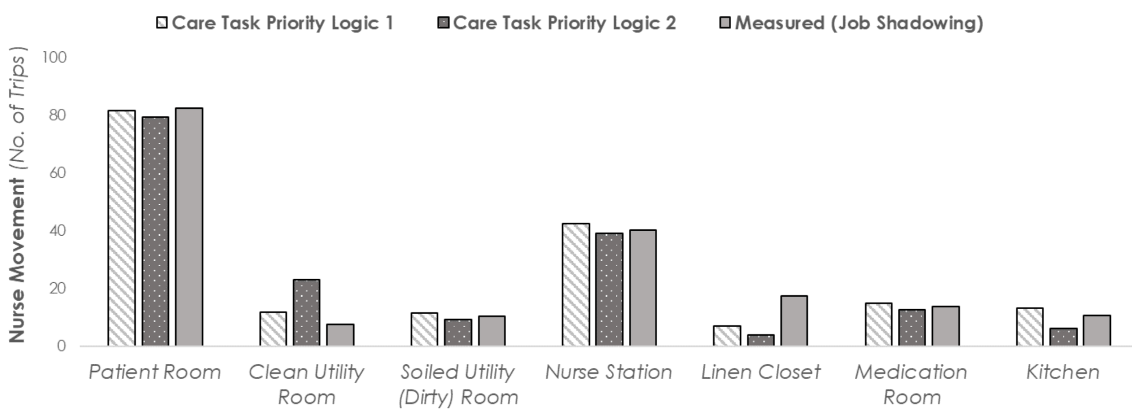

Figure 13 represents the movement of simulant-nurse, following task priority rank sequence1 and 2, and actual nurse, measured via job shadowing study

MISSCARE Survey – The response rate for the survey was 39% (n = 18), 77% of whom identified themselves as females. Respondents had 8 to 20 years of experience as an RN (58%). The highest educational degrees were a bachelor's degree (70%), college diploma (24%) and master's degree (6%). The MISSCARE Survey was used to validate:

- Nurse's perception of Missed Care tasks
- Nurse's perception of Missed care delivery time
- Nurse's perception of the percentage division Missed Care tasks

1) Nurse's perception of Missed Care tasks – The DES model reported a 'total missed care' of 25 tasks (SD = 1.2; Range = 22 to 26.3 tasks) and 26 tasks (SD = 3.22; Range = 22.8 to 30 tasks) following 'task priority rank sequence 1 and 2' respectively. The 'nurse's perception of missed care tasks' as reported by the MISSCARE survey was 18 tasks. An overall ICC = 0.87 was observed between simulation and real-world outcomes. Detailed results are illustrated in Table 7.

2) Nurse's perception of missed care delivery time – The DES model reported a missed care delivery time of 2.4 hours (SD = 0.28; Range = 2.3 to 2.7 hours). The nurse's perception of missed

care delivery time was 1.9 hours (SD = 1.5; Range = 1.6 to 2.6 hours). An overall ICC of 0.85 was observed between simulation and real-world outcomes. Detailed results are presented in Table 7.

3) Nurse's perception of the percentage division Missed Care tasks – The DES model reported the highest percentage of 'missed care' tasks as 'non-patient care' (24%), 'evaluation' (20%), 'assessment and planning' (16%), and lowest percentage of 'missed care' tasks: 'admission' (0%), 'medication' (1.1%), 'consultation' (3.8%). For MISSCARE survey, as reported by respondents, the highest percentage of 'nurse's perception of missed care' tasks were: 'non-patient care' (36%) followed by 'assessment and planning' (16%) and 'evaluations (14%). The lowest percentage of were 'admission' (0%), 'discharge' (0%), and 'consultation' (0%). An overall Spearman rank order correlation coefficient of 0.78 was observed between simulation and real-world outcomes. Detailed Spearman rank order correlation results are presented in Table 7. Table 8 show the detailed percentage division of missed care delivery time.

Table 8 illustrates the percentage division of Missed care tasks for the Simulant-nurse (following task priority rank 1 and 2), and Nurse's perception from the MISSCARE Survey

Simulant-nurse (DES Model)					**Actual Nurse**	
Rank	**Task Priority Rank Sequence for Focus Group 1**	*% of tasks*	**Task Priority Rank Sequence for Focus Group 2**	*% of tasks*	**Nurse's perceptions of Missed Care (MISSCARE Survey)**	*% of tasks*
1	Non-patient care	23%	Non-patient care	20%	Non-patient care	24%
2	Evaluation	22%	Evaluation	20%	Assessment and Planning	13%
3	Assessment and Planning	17%	Assessment and Planning	18%	Evaluation	12%
4	Teaching and Emotional Support	12%	Hygiene	15%	Elimination	8%
5	Other Direct Nursing Care	11%	Other Direct Nursing Care	11%	Teaching and Emotional Support	8%
6	Elimination	5%	Elimination	2%	Other Direct Nursing Care	8%
7	Hygiene	3%	Nutrition	3%	Nutrition	8%
8	Nutrition	2%	Teaching and Emotional Support	3%	Activity	6%
9	Activity	1%	Activity	2%	Hygiene	6%
10	Discharge	1%	Discharge	1%	Vascular Access	3%

11	Treatments	1%	Treatments	1%	Treatments	2%
12	Vascular Access	1%	Vascular Access	1%	Medication	1%
13	Medication	1%	Medication	1%	Vital Signs	1%
14	Vital Signs	1%	Vital Signs	1%	Discharge	0%
15	Admission	0%	Admission	0%	Admission	0%
16	Consultation	0%	Consultation	0%	Consultation	0%

4.4 Discussion

This chapter addresses the challenge of model validity for simulation-based research (SBR) raised by Lamé & Dixon-Woods (2018), by presenting an approach to creating valid computerized simulation model revealed quantifiable measures of quality of care and nurse workload. Previously, DES has been used to model patients as a 'product flow' in a production system, where a patient stops at several stations to receive care. Modeling through the perspective of the worker has the potential to improve healthcare system (Neumann et al., 2018). Therefore, this adaptable modelling approach uses the perspective of nurses to model the process of care delivery. This offers insight to healthcare system by accurately quantifying nurse workload and quality of care under different technical design and operational policies. The modelling approach created has the potential to be used as a proactive decision support system that assists policymakers, healthcare managers, architects and other stakeholders, to devise technical design and operational policies that assist in improving the quality and safety for both, healthcare professionals and patients.

4.4.1 Adapting the DES Model to Medical-surgical Unit

To validate this research, the simulation model was adapted to a medical-surgical unit. A medical-surgical unit was selected because these types of units employ the largest proportion of acute care nurses (Canadian Institute of Health Information, 2017). The model in-data and the external field data were collected from the same inpatient unit to create consistency and make validation more precise.

In-data Validity – Better in-data leads to a better output (Sterman, 2002). More comprehensive inputs were used for this study in comparison to previous works Qureshi et al., (2017; 2019). Historical patient care data was taken for one year because the GRASP data fluctuates throughout the year. The average compliance rate of 86% was well over the quality standard of 75%. Having said that, this model is slightly underestimating; If a compliance rate of a 100% was observed, then the task frequency will also increase slightly which evidently will increase indicators of missed care as well. The floor plan of the same medical-surgical was measured by the research team and then re-created online. The model can be easily adapted to test changes in compliance rate and even a different floorplan on missed care (quality of care).

The programming logic was refined based on input from the staff nurses participating in two focus group sessions. A consensus approach was used to create two task priority rank sequences. We tested both task priority rank sequences that emerged and the logics resulted in generally similar system behaviours although a difference of up to 7% was observed in the distribution of missed care. The dual logics provided an opportunity to test the impacts task priority rank sequence in terms of nurse workload and quality of care. Given that nurses may have different priority rank sequences (Hendry & Walker, 2004), this computerized simulation can be used to test various task priority rank sequences to determine the optimal priority setting to achieve quality of care with decreased workload.

The *Internal validation* is used for quality control and calibration purposes of the model which is critical when the DES model is adapted to any specific inpatient unit. The tests reported in the development of this approach were adapted from Sterman (2002) which do not require excessive reprogramming, nor do they require extensive time. As a result, computerized simulation models can be highly desirable to the stakeholders as the information can be extracted in a timely manner to support decision making. While the study adapted the DES model to a medical-surgical unit, this approach can be adapted to other acute care units such as CCU, ICU, neuro units etc., using the same methodology, to reveal accurate quantifiable measure of workload and quality of care to patients. However further research is required to affirm this.

4.4.2 External Validation from Field Study

The results of three external validation tests provided further evidence for the validity of the modelling approach. Testing included the step counter test, nurse job shadowing and the MISSCARE survey.

The *step counter test* yielded a difference of 5.6 to 11%, specifically, 0.4 to 0.5 km (524 to 525 steps) between the simulant-nurse and actual nurse. This decrease may be attributed to using the standardized time duration set by the GRASP system in the simulation model. Experienced nurses tend to work faster than standardized times (Tabak, Bar-Tal, & Cohen-Mansfield, 1996) and therefore are able to attend to more care tasks in a shift. As a result, the distance walked increased for actual nurses. In addition, it was observed during the 'nurse job shadowing' study that nurses often multitask. In addition to this, it was observed during nurse job shadowing that RNs would go to the *linen* closet and gather the supplies for all their assigned patients and drop these off to each patient's room one by one. Whilst the medical-surgical unit protocol does not allow this because bringing other patient's linen to other patient rooms might infect the material and make the other patients more susceptible to infections and viruses. There seems to be a trade-off as nurses are trying to accommodate an overload situation to best serve the care demands of the patients that may impact the quality of care. Such trade-offs can *easily* be quantified in terms of 'distance walked', 'missed care' and 'care task waiting time' for patients etc. Quantifying these trade-offs can lead to testing and developing policies/protocols that caters to the needs of both patients (quality of care) and nurses (workload), using this nurse-focused simulation model. Hendrich et al. (2008) did a time and motion study at 36 hospitals where they quantified the distance walked by nurses for a 10 hour shift. Since the DES model reports a 12-hour shift; a running average was taken for 'distance walked by the simulant-nurse'. The range of these averages were found consistent with the range of distance walked by actual nurses, as reported by Hendrich et al. An ICC analysis showed an excellent agreement of 0.92 to 0.96 (overall 0.972) between the simulation results (whilst following task priority rank 1 and 2), and field study measurement (FitBit™). Thus, validating the indicator – 'distance walked by simulant-nurse'.

Nurse job shadowing – The highest number of trips were made to the 'patient rooms', followed by 'nurse station' and 'medication room'. This was found consistent for all conditions of the simulation following both task priority rank logics and during job shadowing. This included both direct and indirect trips made to these rooms. A difference of 0.85% to 6% can be observed between simulation and job shadowing with the exception of 'linen closet' and 'clean utility room'. A 45% increase in one-way trips (both direct and indirect) made to 'linen closet' was observed because the medical-surgical unit had two 'linen closets', located at a close proximity across all rooms in the unit to create less walking for the nurse. The nurses often had to make trips to both locations because some of the linen materials were not available in one of the linen closets. Instances like these led to increased one-way trips to the 'linen closet', during job shadowing. This nurse-focused simulation model can be used to quantify how frequently items need to restocked in the linen closet or, the addition of a third linen closet or, to *test* the location of all linen closets in terms of 'distance walked', 'missed care' and 'care task waiting time' for patients. In addition, this DES model can be used to test the impact of different unit layouts in terms of workload and quality of care. Similarly, a 36% decrease in one-way trips made to 'clean utility room' were observed in the nurses as compared to the simulant-nurse possibly due to multitasking. An ICC analysis showed excellent agreement between the simulation results and field study measurement (FitBit™). An ICC showed an excellent agreement of 0.93 to 0.95 (overall 0.99). Thus, validating this indicator – 'simulant-nurse's movement'.

MISSCARE Survey – The DES model reported the following indicators of missed care: total missed care tasks, percentage division of missed care, and missed care delivery time. The MISSCARE survey yielded nurse perceptions of the same three indicators.

For 'total missed care', an ICC analysis showed optimal agreement between the simulation results (whilst following task priority rank sequence 1 and 2), and MISSCARE survey. An ICC of 0.87 was observed between the simulation results (whilst following task priority rank sequence 1 and 2), and MISSCARE survey. Thus, validating this indicator – 'total missed care'.

The highest 'percentage division of missed care' as reported by the simulant nurse and actual nurse was 'non-patient care'. This was found consistent with the RN4CAST study done by Ausserhofer et al. (2014) across 488 hospitals in Europe. Thus, providing face validity. In addition to this, the Spearman rank order correlation showed optimal agreement (overall 0.78) between the simulation results (whilst following task priority rank sequence 1 and 2), and MISSCARE survey. Thus, validating the missed care indicator 'percentage division of missed care'.

The DES model reports a 'missed care delivery time' of 2.3 to 2.7 hours. This range was found consistent with the nurse overtime as reported by Griffiths et al. (2014). Thus, adding face validity to this indicator. During job shadowing, all RNs reported that an overtime of 2 hours is very common in a 12-hour shift. This can be hazardous as the Australian Nursing Federation (2009) reports that the prospect of making an error increases significantly after working for more than 12.5 hours. This further demonstrates that current polices do not support the safe workload for nurses and needs to be managed effectively, as it is impacting the quality of care. ICC showed optimal agreement (overall 0.85) for 'missed care delivery times between the simulation results (whilst following task priority rank sequence 1 and 2) and MISSCARE survey. Thus, validating this missed care indicator – 'missed care delivery time'.

The external field study showed an agreement of 71% to 87% between simulation and MISSCARE survey outcomes. This can be attributed to MISSCARE survey reporting the 'perception' of nurse, and peer-reviewed research has shown a disconnect between perception and actual observation (Sale et al., 2010).

Current healthcare system design – The DES models a 12-hour shift with no breaks while in real-life, nurses are given a cumulative 1-hour break. The DES model is therefore underestimating the levels of actual missed care. Regardless of this underestimate, indicators of missed care are illustrating – nurses *cannot* physically deliver the volume of care required by their patients in the shift time allotted. This is supported by the overtime stats in Canada, where paid and unpaid overtime increased from 19 million dollars to 20 million dollars (Canadian Federation of Nurses Unions, 2015, 2017c). This raises issues regarding the need for short-cuts and rushing with consequences of nurse fatigue and error making. Research has shown that delayed care leads to the deterioration in quality of care and patient safety, in some cases death may also occur (Meischke, THo, Eisenberg, Mickey, Schaeffer, & Larsen, 1995; Weissman, Stern, Fielding, & Epstein, 1991). The proposed approach to creating validated simulation models can be used to proactively test strategies addressing workload in order to quantify the impact on 'missed care' and 'waiting time' to receive care, as measures of quality of care.

4.4.3 On the Issue of Model Validation

The issue of model validity can be compared to the validity of 'self testing blood glucose monitoring devices' (glucometer). Do they provide highly accurate results? No (Kanji et al., 2005) but these devices are frequently used in domestic homes and clinics to gain some insight about the pattern of glucose levels. In the domain of aviation – 'airborne weather radar' use simulation and modelling to predict weather. These are not very accurate devices (Werth, 2014), but they are still heavily used by pilots/control tower personnel to gain insight to the pattern of the weather ahead. The information extracted from these devices are taken with caution while considering the overall pattern. These devices were validated at inception stage and are not validated every time they are used, mainly, because it will defeat the overall cost-benefit of using these devices. They are however calibrated by means of a reboot at the start of each trial. Similarly, this computerized simulation model does not need to be validated for every experiment. However, models need to be calibrated by means of internal validation checks, which is not time consuming.

Similar to 'self testing glucose monitoring device' and 'airborne weather radar', specific "measures" extracted from the model should be done with caution (Sterman, 2002). Research should be done on the level of detail needed. If each modelling case needs extensive field validation then the cost for using these model raises cost benefit issues i.e. the cost and time of model validation will be more than the cost of doing trial and error, thereby, losing the original goal where models have the potential to reduce costs (Banks et al., 2005; Gunal & Pidd, 2010). If extensive time is spent on validation of each operational design (research question), the system may change by the time a tool is validated and the window to reap the benefits of simulation will be lost. You can not expect a map of North America to reveal every bump in the road. Therefore, one must not let perfect be the enemy of good (Earle & Ganz, 2012). Validated models are desirable to the knowledge users and stakeholders - *only* - if the information extracted can be made available in a timely manner (Sargent, 2013; Sterman, 2002). As along as simulation models are precise and are sensitive to change, they can be deemed acceptable to use (Schoeller, 1980), but still used with caution. The validation checks done in the creation of this modeling approach satisfy the precision, sensitivity and accuracy of the model. Therefore, the modelling approach described can be applied to create models of similar inpatient units and will also yield accurate results. However, the sensitivity and precision of the model must be evaluated via quick internal validation checks.

4.4.4 Model Implications and Applications

The use of a validated simulation model has the potential to shift healthcare system design towards a more evidence-based approach using quantitative indicators. These models integrate available evidence and data to help understand complex system dynamics including, nurse and patient outcomes. Incorporating a focus on the healthcare professional can influence safety of both patients and nurses. (Carayon, Xie, et al., 2014), workload management and quality in daily operations (Norris, 2012; Russ et al., 2013). This adaptable modelling approach offers a promising strategy to quantify the impact and test newer technical design and operational decisions on a range of nurse and patient outcomes.

Model users –This nurse-focused modelling approach can support the work of multiple users. *Architects* can use the models to improve the layouts of inpatient units to promote more efficiency in nurses' work. *Policy makers* can test the consequences of technical design decisions and policy trade-offs such as testing nurse-patient ratios when attending to more acute patients, and can even be used to test the effect of varying shift length (8-hour and/or 12-hour shift) in terms of nurse workload and quality of care. H*ospital managers* can use the model to test strategies to create safer work environments for healthcare practitioners (such as nurses) while the *charge nurses* could compute ideal location-based patient-bed assignments. More research is needed regarding usability and utility for these stakeholders.

Adaptability – While the study applied the DES model to a medical-surgical unit, this nurse-focused modeling approach is universal and can be adapted to other acute care units using the same methodology. This makes this modeling approach very desirable for healthcare managers, policymakers and other stakeholders. However, further research and testing is required to affirm this.

Future work includes expanding indicators for nurse workload such as quantifying the biomechanical load for shoulder and lumbar areas, making use of location-based patient bed assignment and incorporating nurse competency levels. Other quality of care indicators to consider in the computerized model would include error rates and adverse events. A third area of inquiry would be to capture nurse-specific outcomes such as fatigue.

4.5 Conclusion

This research provided an approach to developing valid computerized models of the process of care delivery that quantify nurse workload and quality of care. An ICC of 0.99, 0.99, 0.87, 0.85 shows an excellent agreement between the modelling and field study outcomes for 'distance walked by the simulant-nurse', 'simulant-nurse movement', 'total missed care' and 'missed care delivery time'. A Spearman rank correlation of 0.78 shows good consistency for 'percentage division of missed care' between simulation outcomes and external field study outcomes. This simulation model provides quantifiable evidence that current healthcare system polices and design increase the work demands of nurses (distance walked by simulant-nurse = up to 11.1km; direct care time = 10.7 hours). Thus, making it not possible for the nurse to complete their care tasks (missed care increased up to 31 tasks). As a result, the quality of care is compromised (missed care increased up to 31 tasks). This approach to creating valid computerized model can be used as decision support system to proactively test and quantify the impact of newer design policies and their significant trade-offs, in terms of nurse workload and quality of care.

4.6 Ethics approval

The study was approved by the *Ryerson Research Ethics Board (REB # 2017-340)* and *University Health Network's REB Coordinated Approval Process for Clinical Research (CAPCR # 17-6084)*.

CHAPTER 5

GEOGRAPHICAL PATIENT-BED ASSIGNMENT

Chapter 4 presented a approach to creating valid nurse-focused simulation model. The aim of this chapter was to extend the validated nurse-focused modelling approach by further testing the DES model on other technical design and operational policies. As illustrated in Chapter 1, geographical patient-bed assignment is an important driver of workload. This chapter quantifies the impact of different geographical patient bed assignment on nurse workload and quality of care. The focus here is to create an adaptable modelling approach and demonstrate its application in the case of a real healthcare system setting. This research supports the prospective ergonomics agenda by providing a tool that can change the operational approach from being 'reactive' to being 'proactive' (Robert & Brangier, 2012) .

This chapter addresses RQ 4 – *How do changes in geographical patient-bed assignment impact the distance walked by the simulant-nurse and other indicators of nurse and patient outcomes?*

5.1 Methods

The simulation model was created using Rockwell (ARENA), DES modelling software. The DES model simulates the process of care delivery by nurses under different work design conditions. Inputs to the DES model included indicators from healthcare system (inpatient unit) design and policies, such as 'hospital unit floorplan'; 'patient care data'; 'nurse's operating logic'; 'nurse's walking patterns'. Modelling outputs included indicators of nurse workload: 'total distance walked by the simulant nurse'; 'task in queue'; 'direct care time'. Indicators of quality of care included: 'missed care'; 'care task waiting time'. These are further described in page 84 (section 5.2.5). As a case example, this research adapted the demonstrator model to a medical-surgical unit from a metropolitan area teaching hospital in Toronto, Canada. A medical-surgical unit was selected because the largest proportion of acute care nurses across Canada (24%) work in this area (Canadian Institute of Health Information, 2017). Figure 14 provides an overview of the model.

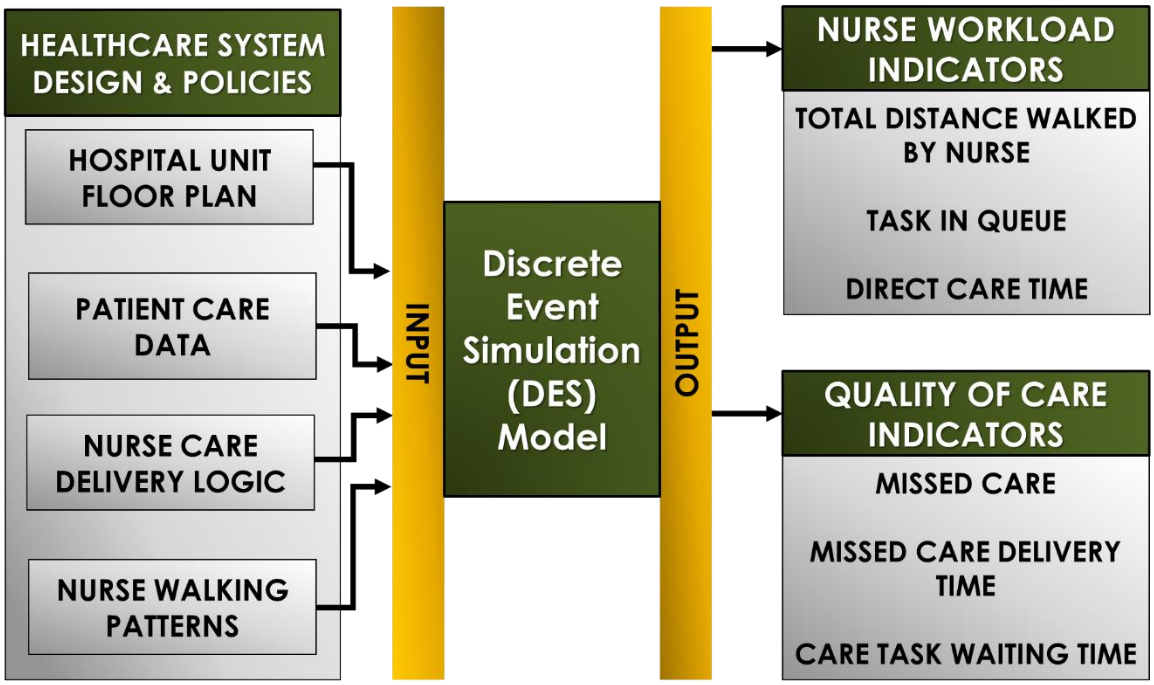

Figure 14 represents an overview of the DES model used for testing Geographical patient-bed assignment. Inputs to the model are depicted as healthcare design and policies indicators and outputs include indicators of nurse workload and quality of care

5.2 Model Inputs

5.2.1 Hospital Unit Floorplan

The DES model is run on a hospital floor plan from the selected medical-surgical unit. The physical dimensions of the unit were measured using a Bosch (GLM30 100 Ft.) Laser Measure. Figure 15 provides the graphical representation of the nurse-centered inpatient unit. The unit consisted of seven single bedrooms, nine double bedrooms and two quad patient bedrooms, a clean utility room, a dirty utility room, two linen carts, a kitchen, shower room and a nurse station.

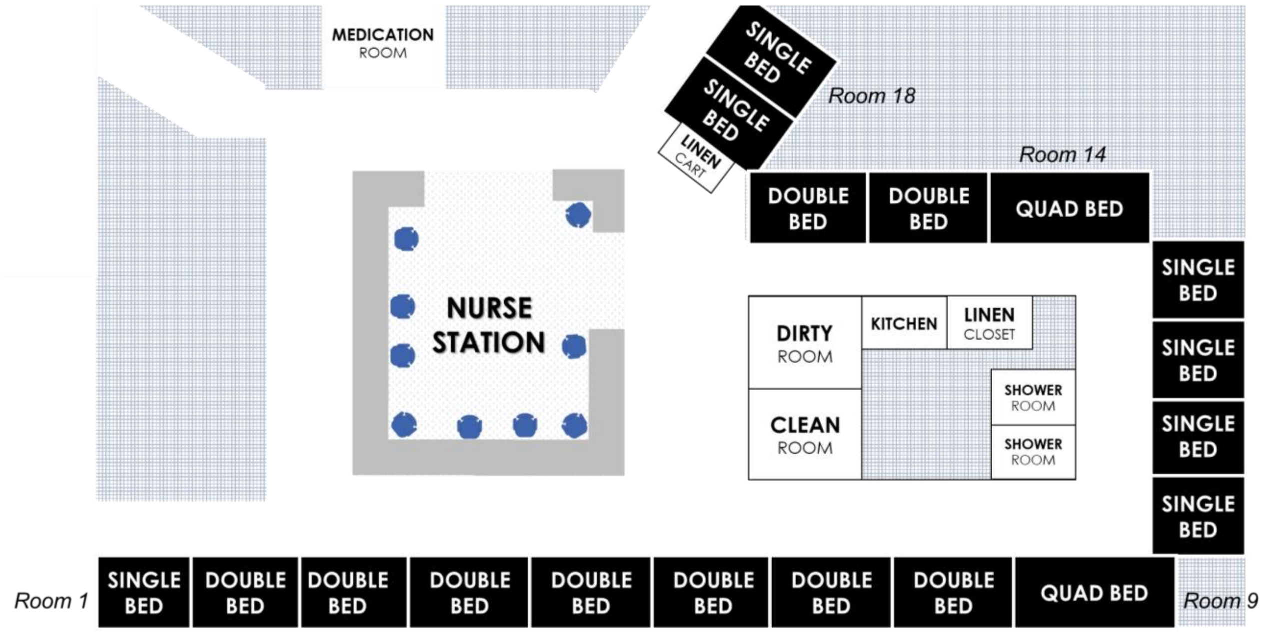

Figure 15 shows the floorplan from the Selected Medical-surgical Unit (not to scale)

5.2.2 *Patient Care Data*

Patient care data specifies the patient care tasks that are completed daily by the nurses for their assigned patients that are collected using institutional care delivery records. An anonymized patient care dataset was obtained as part of a workload and cost center report system software called Infor, more commonly known as *GRASP system* (Grace Reynolds Application of the Study of PETO). This anonymized dataset was obtained for a period of one year, from the selected unit. The dataset contained *task information* (task frequency; task duration) pertaining to each care task group and associated sub-tasks for this specific patient care unit. For instance, care task group 'Assessment and Planning' has a sub-task 'Braden scale assessment'. '*Task frequency*' included the task count – how frequently a certain task was performed. *'Task duration'* estimated the time to complete a certain task. GRASP uses standardized task durations. In an effort to reduce the volume of sub-task programming, modelling was done at the task group level. Therefore, a frequency weighted average of GRASP's standardized time was taken. Table 9 contains the frequency weighted task duration for all tasks included in the model.

Table 9 illustrate the DES Model Care Task Groups, Priority level (1 = Highest; 6 = Lowest), Scheduling Type and Time Duration (Frequency weighted).

Care Task Group	Priority level (rank)	Care Task Scheduling type	Time Duration (min)
Assessment and Planning	1	Random intervals	2.58
Vital Signs	1	Random intervals	1.58
Medication	3	Random intervals	15.03
Admission	2	Random intervals	16.05
Vascular Access	4	Random intervals	6.65
Activity	4	Random intervals	35.38
Treatments	5	Random intervals	5.7
Nutrition	5	Random intervals & Scheduled intervals (8AM, 12PM, 5PM)	8.62
Consultation	6	Random intervals	5
Hygiene	6	Random intervals + Scheduled interval (8:00AM)	10.27
Elimination	6	Random intervals	9.73
Discharge	7	Random intervals	10.7
Evaluation	7	Random intervals	3
Teaching and Emotional Support	7	Random intervals	20.89
Other Direct Nursing Care	8	Random intervals	14.54
Non-patient care	9	Random intervals	7.1

5.2.3 Nurse Operating Logic

Nurse operating logic consists of: 1) *care task priority rank,* 2) *care task scheduling logic* and 3) *care delivery logic,* developed by means of a *focus group session* with 15 RNs, having four to 23 years of experience in the selected medical-surgical unit. The inclusion criteria were that they must be fluent in English and an RN/RPN with 2 years of experience in medical-surgical unit. The focus group sessions identified the care delivery priority sequence and care delivery logic for various nursing care tasks. Participants had 2 to 23 years of experience in the medical-surgical unit with either a bachelor's or master's degree in nursing.

Care task priority rank denotes the different priorities rank for each care task. A consensus approach was used in the focus group session to formulate the *priority rank* for all care tasks. The participants in the focus group session considered the urgency and importance of the care task based on their professional experience (Hendry & Walker, 2004).

Care task scheduling entails the care tasks that follow a schedule or if they occur randomly during the shift. In this model, only nutrition (8am, 12pm, 5pm) and hygiene (8am), care tasks are scheduled. Table 9 represents the different care task scheduling types programmed in the model. A consensus approach was also used to formulate the *care task scheduling.*

Care delivery logic determines which care task the simulant nurse must perform with respect to care task priority. All participants unanimously agreed that they would perform the highest priority task at the shortest distance. This assisted with the case when a simulant-nurse has to perform multiple care tasks at the same time with the same priority rank. The DES model is programmed to complete the highest priority task at the shortest distance with respect to simulant nurse's current geographical position. It is anticipated that other groups of nurses may identify different care task priorities and the DES model can easily be adapted to test other logic rules.

5.2.4 Nurse walking patterns

Nurse walking patterns refer to the walking sequence of the care delivery tasks (task list generated from GRASP). These walking patterns were developed in consultation with two subject matter experts (SME) with five to eight years of experience on the selected unit. A Methods Time Measurement (MTM) tool was used to construct the walking speed in the simulation model (Myny et al., 2010). Table 10 shows the walking pattern of two sample care tasks.

The proposed simulation methodology is an adaptable modelling approach that can be modified to address a specific research question and context. Each of these modelling inputs (patient care data, hospital unit floorplan, nurse operating logic and nurse walking patterns) can be adapted to specific contexts.

Table 10 - An example of the walking pattern for nurses while performing care tasks. The 'initial location' is the last geographical location of the nurse after completion the previous care task or the nursing station at the start of the shift.

Task Group	Care Task	Walking Pattern
Vascular Access	IV Start	Initial location -> Medication Room -> Patient Room -> Nurse Station
Elimination	Shift Fluid Balance	Initial location -> Patient Room -> Nurse Station

5.2.5 Modelling Outputs

The DES model outputs included indicators of nurse workload and quality of care.

Nurse workload indicators included: *'Total Distance walked by Simulant Nurse', 'Task in queue' and 'Direct care time'*. *'Total Distance walked by Simulant Nurse'* was the cumulative distance walked by the simulant nurse for one 12-hour shift. *'Task in queue'*, a mental workload indicator, operationalized as the average number of pending tasks in a queue to be performed by a nurse (Potter et al., 2009). *'Direct care time'* entailed the total time spent by nurses while delivering care as defined by the GRASP data.

Quality of care indicators included: *'Missed care'*, *'Missed direct care time'*, and *'Care task waiting time'*. *'Missed care'* referred to the number of care tasks left undone at the end of the simulant nurse's 12-hour shift. In practice, these care tasks are not necessarily missed – most of these care tasks are completed either by the nurse on the next shift or the present nurse who worked overtime beyond the end of the shift. *'Care task waiting time'* was the average time before a care task is delivered.

5.2.6 Average Inter-Bed distance (IBD) and Average Bed-Nurse Station distance (BND)

In this research, geographical patient-bed assignment is operationalized using the average *inter-bed distance* and average *bed-nurse station distance*.

Inter-bed distance (IBD) is the average distance between all patient beds assigned to one nurse. It is an indicator of clustering of assigned beds. In this research, a total of five patient beds were assigned to one nurse, the most common nurse-patient ratio in acute care (Corchia et al., 2016). The previous chapter quantified the nurse movement and provided evidence that the nurse station and patient rooms were the two most frequently visited area for nurses during a 12-hour shift. Making these direct contributors to nurse workload. Therefore, Bed-nurse station distance (BND) was also tested. BND is the average distance between the assigned patient beds and the nurse station. BND is an indicator of how far/close the assigned patient beds are from the center of the unit. In the selected medical-surgical unit, nurse station was at the center of the unit. Which is typical in most in-patient units. This demonstrator model can easily be adapted to test alternatives where nurse-station is not at the center of the unit. Mathematical calculations of IBD and BND are represented below:

$$\text{Inter-Bed distance } \textit{(in meters)} = \sum_{i=1} \frac{P_i \rightarrow P_{n-i}}{n}$$

$$\text{Bed-Nurse Station distance } \textit{(in meters)} = \sum_{i=1} \frac{N_s \rightarrow P_{n-i}}{n}$$

Where,

P= Distance between any *two patient beds*

N_s = Distance between the *nurse station* and a *patient bed*

n = Total number of patient beds assigned to one nurse (n=5 in this case)

Table 11 illustrates the patient bed assignments studied. These patient bed assignments were developed by drawing on the knowledge experienced nurses along with assumed best-worst case scenarios where the five assigned patients were close together (best case) or as far apart as possible (worst case). Typical nurse bed-assignments locations for nurses were selected via interview with an 11 RNs with five to nine years of experience in the selected unit. The BND of these nurse bed-assignments were translated to 20.4, 21.5, 25.6, 27.6, 30 and 31.3 meters. In this study, the baseline case of 21.5 meters of BND was selected as this assignment was experienced frequently by all the participants.

5.2.7 DES Model Testing

The DES model was run for 365 days on all 15 patient-bed assignment conditions. The model was run for only ‘day’ shifts, as workload is the highest for nurses during this shift. Each shift was programmed as 12 hours in length, in this case, a standard in North America. To reach an optimal modeling state, a model warm up time was estimated to be 28 days, using Welch’s Method (Hoad et al., 2008). Data from 337 shifts was analyzed and 28 shifts of warm up time data was discarded. Multivariable regression analysis was conducted for all experimental conditions to establish significant predictors (IBD and BND) of nurse workload and quality of care indicators.

*Table 11 – Experimental conditions in this study, where, * represents typical patient bed assignments of an experienced nurse*

Trial	Inter- Bed to Nurse Station Distance (m)	Inter-Bed Distance (m)	Patient bed locations	Room numbers
1	19.3	12.9	2p x 2 Double bedroom 1p x 1 Single bedroom	Room 1 to 3
2	19.9	18.1	1p x 1 Double bedroom 1p x 4 Single bedrooms	Room 16 to 20
3*	20.4	11.3	1p x 5 Single bedrooms	Room 9 to 13
4* (baseline case)	21.5	20.0	2p x 2 Double bedroom 1p x 1 Double bedroom 1p x 1 Single bedroom	Room 2, 4, 5, 16
5*	25.6	11.9	2p x 1 Double bedroom 1p x 1 Double bedroom	Room 3 to 5
6*	27.6	11.9	2p x 2 Double bedroom 1p x 1 Double bedroom	Room 4 to 6
7*	30.0	33.1	1p x 1 Quad bedroom 2p x 2 Double bedroom	Room 3, 9 and 16
8*	31.3	42.3	1p x 3 Single bedroom 1p x 2 Quad bedroom	Room 1, 9, 14, 17 and 20
9	31.6	40.5	1p x 3 Single bedroom 1p x 1 Double bedroom 1p x 1 Quad bedroom	Room 1, 5, 12, 14 and 20
10	31.6	9.4	4p x 1 Quad bedroom 1p x 1 Single bedroom	Room 13 and 14
11	32.3	40.5	1p x 2 Single bedroom 1p x 1 Double bedroom 1p x 2 Quad bedroom	Room 1, 5, 9, 14 and 20
12	34.9	10.3	4p x 1 Quad bedroom 1p x 1 Single bedroom	Room 9 and 10

5.2.8 Model Verification

This chapter made use of the verification techniques outlined by Sargent (2013). *Degenerate testing* – the degeneracy of a model's behaviour is checked by running the simulation model on conditions that will produce near zero output. The demonstrator model was run with only one patient assigned to a nurse with 90% reduction in task frequency. The direct care time was reduced to <1 hour. The demonstrator model responded as expected. Thus, verifying the programming of this model

Repeatability and Reproducibility test – The ability of a model to produce similar results under similar conditions when the model is run of different devices by different operators. The demonstrator model was run on 5 different devices (3 PCs and 2 Mac devices). Rockwell (ARENA) is not supported on Mac therefore, a windows emulator was installed. The demonstrator model produced similar results (<1% variability) across all devices. Thus, verifying the programming of this model

Animation and graphics test – This test allows the programmer to observe if the model is following the operational logic, whilst running simulation. An animation component was built inside the demonstrator model. Whist running simulation, it was observed that the simulant-nurse was following the operational logic programmed into the model. The model was programmed to deliver the most urgent (high priority) care at the closet distance; the demonstrator model was following this logic. Thus, verifying the programming of this model

5.3 Results

This adaptable DES modelling approach successfully quantified the effects of changing the geographical patient-bed assignments in terms of nurse workload and quality of care. Detailed results are presented below:

5.3.1 Nurse Workload Indicators

Total Distance walked by Simulant Nurse – As illustrated in Table 12, an increase in distance walked can be observed except for the average BND of 31.7 meters. For the baseline case, the simulant nurse walked 9.73 km during the 12-hour shift. A relative difference of up to +21 was observed Multivariable regression analysis reported the following regression equation:

$$Y_{\text{(DISTANCE WALKED)}} = 6.4 + 0.13\, X_{\text{BND}} + 0.02\, X_{\text{IBD}}$$

Where, $F(2,9) = 369.37$, $p<0.00$), with an R^2 of 0.98. where $Y_{(DISTANCE\ WALKED)}$ is coded as Kilometers and, X_{BND} and X_{IBD} are coded as meters. Both BND and IBD were significant predictors of 'Total Distance walked by Simulant Nurse'.

Task in Queue – As illustrated in Table 12, an increasing trend can be observed No. of Tasks in Queue increase as bed assignments shift from best to worst case scenarios except for the BNDs of 19.3, 19.9 and 21.5 meters. A range of 11 to 13.8 tasks were waiting to be performed by the simulant nurse. For the baseline case, the simulant nurse had 12.62 tasks waiting to be performed. A relative difference of up to 10% were observed. Multivariable regression analysis reported the following regression equation:

$$Y_{(TASK\ IN\ QUEUE)} = 9.6 + 0.11\, X_{BND} + 0.01\, X_{IBD}$$

Where, $F(2,9) = 81.8$, $p<0.00$), with an R^2 of 0.94. where $Y_{(TASK\ IN\ QUEUE)}$ is coded as tasks and, X_{BND} and X_{IBD} are coded as meters. Both BND and IBD were significant predictors of 'Task in Queue'.

Direct care time – The simulant nurse delivered care for a range of 10 to 10.4 hours A relative percentage difference of -8% was observed. Multivariable regression analysis reported the following regression equation:

$$Y_{(DIRECT\ CARE\ TIME)} = 12.1 - 0.05\, X_{BND} - 0.007\, X_{IBD}$$

Where, $F(2,9) = 155.05$, $p<0.00$), with an R^2 of 0.97. where $Y_{(DIRECT\ CARE\ TIME)}$ is coded as hours and, X_{BND} and X_{IBD} are coded as meters. Both BND and IBD were significant predictors of 'Direct care time'. Detailed results for the different geographical patient-bed assignment condition is illustrated in Table 12.

5.3.2 Quality of Care indicators

Missed Care – The highest missed care were 47 tasks that were observed for the patient-bed assignment with a BND of 32 meters. A relative percentage difference of up to 27% was observed. Multivariable regression analysis reported the following regression equation:

$$Y_{(MISSED\ CARE)} = 13.5 + 0.9\, X_{BND} - 0.10\, X_{IBD}$$

Where, $F(2,9) = 81.8$, $p<0.00$), with an R^2 of 0.97. where $Y_{(MISSED\ CARE)}$ is coded as tasks and, X_{BND} and X_{IBD} are coded as meters. Both BND and IBD were significant predictors of '*Missed Care*'.

Table 12 provides a summary of the Impact of Geographical Bed Assignment on Nurse Workload and Quality of Care Indicators

Trial	Geographical Bed Assignment				Nurse Workload Indicators			Quality of Care Indicators	
	Average Bed-Nurse Station distance *(m)*	**Average Inter-Bed distance *(m)***	**Patient bed locations**	**Room numbers**	**Distance Walked by Simulant Nurse** *km (Δ% base)*	**Tasks in Queue** *task (Δ% base)*	**Direct care time** *hour (Δ% base)*	**Missed Care** *task (Δ% base)*	**Care Task Waiting Time** *hour (Δ% base)*
1	19.3	12.9	*2p x 2 Double bedroom* *1p x 1 Single bedroom*	Room 1 to 3	9.33 (-4%)	11.7 (-7%)	10.91 (0%)	30 (-19%)	0.9 (-5%)
2	19.9	18.1	*1p x 1 Double bedroom* *1p x 4 Single bedrooms*	Room 16 to 20	9.44(-3%)	12 (-5%)	10.90 (0%)	32 (-14%)	0.91 (-4%)
3	20.3	11.3	*1p x 5 Single bedrooms*	Room 9 to 13	9.60 (-1%)	12.2 (-3%)	10.88 (0%)	34 (-8%)	0.92 (-2%)
4 (baseline case)	**21.5**	**20**	**2p x 1 Double bedroom** **1p x 2 Double bedroom** **1p x 1 Single bedroom**	**Room 2, 4, 5, 16**	**9.73 (0%)**	**12.6 (0%)**	**10.87 (0%)**	**37 (0%)**	**0.94 (0%)**
5	25.57	11.92	*2p x 1 Double bedroom* *1p x 1 Double bedroom*	Room 3 to 5	10.03 (3%)	13 (3%)	10.66 (-2%)	40 (8%)	0.96 (2%)
6	27.58	11.92	*2p x 2 Double bedroom* *1p x 1 Double bedroom*	Room 4 to 6	10.59 (10%)	13 (3%)	10.64 (-2%)	40 (8%)	0.96 (2%)
7	30	33	*1p x 1 Quad bedroom* *2p x 2 Double bedroom*	Room 3, 9 and 16	11.09 (14%)	13.5 (7%)	10.15 (-7%)	44 (19%)	0.99 (5%)
8	31.25	42.3	*1p x 3 Single bedroom* *1p x 2 Quad bedroom*	Room 1, 9, 14, 17, 20	11.66 (20%)	13.75 (9%)	10.06 (-7%)	46 (24%)	1.00 (6%)
9	31.61	40.5	*1p x 3 Single bedroom* *1p x 1 Double bedroom* *1p x 1 Quad bedroom*	Room 1, 5, 12, 14, 20	11.75 (21%)	13.81 (9%)	10.04 (-8%)	46.5 (26%)	1.01 (7%)
10	31.69	9.37	*4p x 1 Quad bedroom* *1p x 1 Single bedroom*	Room 13 and 14	10.87 (12%)	13.5 (7%)	10.19 (-6%)	44 (19%)	0.99 (5%)
11	32.2	40.5	*1p x 2 Single bedroom* *1p x 1 Double bedroom* *1p x 2 Quad bedroom*	Room 1, 5, 9, 14, 20	11.76 (21%)	13.8 (10%)	10.04 (-8%)	47.01 (27%)	1.01 (7%)
12	34.9	10.29	4p x 1 Quad bedroom 1p x 1 Single bedroom	Room 9, 10	11.30 (16%)	13.5 (7%)	10.12 (-7%)	44.5 (20%)	0.99 (5%)

Care Task Waiting time – For baseline case, a care task time of 0.94 hour was observed with a range of 0.9 to 1.01 hours. A relative difference of up to 7% was observed. Multivariable regression analysis reported the following regression equation:

$$Y_{\text{(CARE TASK WAITING TIME)}} = 0.79 - 0.006\, X_{\text{BND}} - 0.00069\, X_{\text{IBD}}$$

Where, F (2,9) = 81.8, p<0.00), with an R^2 of 0.94. where $Y_{\textit{(CARE TASK WAITING TIME)}}$ is coded as hours and, X_{BND} and X_{IBD} are coded as meters. Both BND and IBD were significant predictors of '*Care Task Waiting time*'.

5.4 Discussion

Simulation and modelling support the prospective ergonomics agenda (Robert & Brangier, 2012), by providing decision makers with a proactive support system that provides quantitative data to inform system design and management at the unit level. This research provides an adaptable modelling approach that can reveal the quantifiable effects of changing technical design policies such as geographical patient bed assignment on nurse workload and quality of care. Traditional approaches have been limited to modelling patients as a 'product flow' system, similar to manufacturing where a product stops at multiple stations to receive care. While this approach is not wrong, it provides limited insight to quality of care and healthcare professional work demands. The unique feature of this adaptable modelling approach is that it model's the process of care delivery from the perspective of nurses and quantifies nurse workload and quality of care under different operational design policies. Furthermore, this research addresses the need for a tool that can proactively quantify workload and work demands of nurses. Quantifying nurse workload and quality of care opens doors to creating better process improvement strategies. In addition to this, this research offers the ability to proactively test these improvement strategies. Thus, eliminating the need for 'trial and error' and making healthcare professionals work under untested work polices.

5.4.1 Inter-Bed distance vs. Bed-Nurse Station distance

This chapter operationalizes geographical patient-bed assignments as the average inter-bed distance (IBD) and average bed-nurse station distance (BND). Initially, geographical patient bed assignment was operationalized as IBD only. IBD was the average distance between all patient beds assigned to one nurse. Depending on the unit layout, it may be possible when two nurses are assigned to the same bed configuration, but at different locations in the unit i.e. beds that are far/near the nurse station. This mostly happens when there is close cluster of patient beds assigned to a nurse. For instance: one nurse may be assigned to all patient beds in a quad-patient bedroom and a single-patient room that are right next to each other and are located near the center of the unit; the other nurse may be assigned to the same configuration but the assigned patient beds are located far away from the center of the unit. Table 12 illustrates this phenomenon as Trial 5 and 6 both have an IBD of 11.92 meters, where trial 5's bed configuration was away from the center of the unit and Trial 6's was closer to the center of the unit. For both conditions, a difference up to 10% can be observed for indicators of nurse workload and quality of care. To gain more insight to this issue of geographical patient bed assignment, 'Bed-Nurse Station' (BND) was explored where BND is the average distance between each nurse assigned patient bed with the nurse station. Most units have nurse station at the center of the unit, although there may be other configurations where nurse station is not at the center of the unit. The demonstrator model can be easily adapted to test this. This indicator illustrates the distance from the center of the unit to the beds. There may be instances where bed assignments have similar BNDs as in Trial 9 and 10 where the BND was 31.6 meters. In this situation, differences of +8% were observed for indicators of quality of care and nurse workload. This further provides additional support for this indicator. In addition, IBD failed to report identical close clusters of beds assigned to nurse, as mentioned in the above example of Trial 5 and 6. Having said that, this does not make IBD a bad indicator rather IBD provides limited information. Even though BND provides some variability (+8%) for similar bed assignment at different locations, BND cannot be used as the sole indicator for geographical patient bed assignment. In fact, these two indicators should be used in parallel to another. Where, one indicator (BND) provides information pertaining to the distance of beds from the center of the unit (nurse station) and the IBD provides information on how far the beds are from one another. Regression analysis conducted separately for IBD and BND reported R^2 values up to 0.57 and 0.66 respectively, for indicators of nurse workload and quality of care. However, multivariate regression analysis reported R^2 values much higher i.e. 0.94 to 0.98, when both IBD and BND were considered together. This further proves IBD and BND as significant predictors for indicators of nurse workload and quality of care. These results suggest that both BND and IBD should be considered during patient-bed assignment for nurses.

5.4.2 Nurse Workload Indicators

Nurses operate in a work environment with limited autonomy and high demands (Kramer & Schmalenberg, 2008; Skår, 2010). This research quantified these high demands of nursing work. Karasek's 'Demand Control' model (1979) categorizes these low autonomy jobs as high work demand as 'high strain jobs'. Being continuously exposed to high strain jobs lead to MSD, burnout etc. (Gingras et al., 2010; Karasek, 1979; Rizo-Baeza et al., 2018).

'Direct care time ' – Hendrich et al., (2008) conducted a time and motion study in 36 hospitals to quantify how nurses are spending their time. Nurses spend 77.7% of their time in delivering care. The DES model reported similar results where that simulant nurse spent 78.6% of its time in delivering care. When the nurse was assigned to patient beds further from each other and from the nurse-station; all indicators of nurse workload increased, and quality of care decreased. While this result was not surprising, the unique element of the modelling approach is the ability to provide the results in specific quantifiable terms i.e. the size of the impact on nurse workload and patient care quality.

'Distance walked by simulant nurse' – Butt et al. (2004) reports that nurses walk an average of 10.86km in a 12-hour shift. The DES model reported similar findings where the simulant-nurse walked an average of 10.66km (SD = 0.9) for a 12-hour shift across all conditions. The slight increase (1.8%) in the distance walked can be attributed to different patient acuity levels for patients in the unit and unit layout. More importantly, the DES model was able to report a similar pattern.

Lack of consistency between 'Distance walked by simulant nurse' and 'Direct care time' – There is some inconsistency across 'distance walked by simulant nurse' and 'direct care time'. For instance, in trial 11, the simulant nurse walked 11.76 km in a 12-hour shift. Using the walking speed as reported by Cavagna & Margaria (1966), the time to walk this distance would be approximately 3 hours. A difference of <10% is observed where the time spent while delivering care was 10 hours out of a 12-hour shift, 2 hours were spent on walking. This discrepancy can be attributed to the standardized time duration in GRASP data where walking time inside the patient room is already accounted for which could explain the <10% difference. In an interview with the GRASP manager, the GRASP data includes a small portion of walking time inside the patient room characterized as part of delivering care. Since GRASP data was used for the DES model, 'direct care time' included a similar portion walking time inside the patient room, characterized as delivering care. Hence, the slight inconsistency (<10%).

Task in queue – If the simulant nurse was assigned to patient beds further away from the nurse station, the 'distance walked by simulant nurse' increased up to 23%. Since more time was spent walking, there was an observed reduction of 8% on 'direct care time'. As a result, the simulant nurse had up to 10% more 'tasks in queue' contributing to an already increased workload. Therefore, the DES model provides quantifiable evidence that nursing is a high work demand job (Skår, 2010). Where, less optimal geographical patient bed assignment can contribute to excess workload.

5.4.3 Quality of Care Indicators

'*Missed care*' in this case model increased from 30 to 46 tasks from best to worst case scenarios. This range of the care tasks left undone were found consistent with the RN4CAST study conducted by Ausserhofer et al., (2014) across 488 med-surgical units in 12 European countries. While the actual numbers of 'missed care' tasks might seem inflated when compared to the RN4CAST, the DES model reported actual 'missed care' while the RN4CAST study measured nurses' 'perceptions of missed care'. The highest 'missed care' tasks reported in the RN4CAST study were care planning, patient education and comfort/talking, which was found to be consistent with the most areas of 'missed care' identified by the group care tasks categories of the DES model such as: 'assessment and planning' and 'teaching and emotional support'.

Care Task wait time – The simulant nurse when assigned to patient beds that are further away from the nurse station, led to delivery of reduced care tasks. Because the simulant nurse spent more time walking. As a result, the 'care task waiting time' increased by +5% which impacted 'missed care' by increasing up to +26%. Using this computerized modelling approach, the simulation model can help isolate the impact of specific issues.

5.4.4 Methodological Modelling Issues

The current DES model was built on historical patient care data derived from the GRASP report for the selected unit. The GRASP data uses standardized task durations that factors in a personal fatigue delay of 7%. It may be possible that these task durations are inflated for some nurses. Similar to MTM, some people can beat the standard walking speed. The DES model did not account for the variability between a novice and experienced worker as experienced nurses may work faster by multitasking or using other efficiencies. Other model limitations include modelling at the task group level. This helped reduced the programming and simulation run time of the model. While simulating at the task level is possible, there is a trade-off that simulation run time will increase while this small increase in precision may not be worth the extra effort. However, further research is required to affirm this. In addition, during simulation, the width of the hallways remained constant i.e. the hallways were not crowded. In reality, this might not be the case. Most units are overbooked (Parente, Salvatore, Gallo, & Cipollini, 2018), and some patients are placed on beds on the side of the hallway. This may slow down the nurse walking speed or which may lead to additional walking as the nurse may want to avoid that route. Further research is needed to quantify its impact. Future work includes exploring the impact of hallway occupancy, incorporating additional indicators of workload and quality of care such as the number of trips made to each room (example: clean/dirty room, medication room etc.); creating shift-long work patterns of biomechanical load for shoulder and lumbar areas for nursing care tasks with fatigue and error rates; exploring variability by studying the impact of nurse competency levels and the interaction between geographical patient-bed assignment and nurse patient ratio. Despite the sensitivity analysis run on patient bed assignment in this research, the impact of geographical nurse-patient bed assignment on nurse workload and quality of care needs to be further tested on different hospital unit floorplans.

5.4.5 Implications to Healthcare Systems Engineering

This research has the potential to shift the conversation of healthcare system design and nurse workload management towards a more evidence-based use of quantitative indicators. These models integrate available evidence and data to help understand complex system dynamics and the impact on nurse and patient outcomes. This adaptable modelling tool may benefit the *charge-nurse*, by providing a proactive decision support system that can be used to assign the most optimal patient bed assignment to all the nurses on the unit. *Architects* could use this computerized simulation modelling to create optimal floor plans that support nurses in their daily care. *Policy makers*, such as nurse managers and administrators, could improve the current state of nursing by testing newer design policies by proactively quantifying the impact of the policy on work demands for nurses and their relative effect on quality of care before implementation. Quantifying work demands can lead to creating policies that lead to lower work demands thereby potentially reducing injuries, boosting employee morale and satisfaction. This research may offer a safer and more cost-effective alternative to current 'trial and error' methodologies. The model is now ready to be used by decision-makers to better manage nurse workload and on the quality of care.

5.5 Conclusion

In this study, an adaptable modelling approach was created to quantify the impact of choosing different geographical patient-bed assignments on nurse workload and quality of care. As the simulant nurse was assigned to patient beds further from the nurse station, an increase in nurse workload was observed. There was a 23% increase in *'distance walked by simulant nurse'*; a reduction of -8% on *'direct care time'*; a +10% increase in number of *'tasks in queue'*. In addition, quality of care deteriorated with a 5% increase in 'care task waiting time' and 26% increase in *'missed care'*. The model is now ready to start trials with decision-makers in real units on how to better manage nurse workload and their subsequent impact on quality of care.

CHAPTER 6

BIOMECHANICAL LOAD MODELING

This chapter extends the nurse-focused modeling approach developed in the previous chapters by combining DES and DHM to create a time history of biomechanical loads for a nursing shift. As a demonstration case, this chapter reports on the quantification of the impact of changes in geographical patient bed assignment, patient acuity levels and nurse-patient ratio in terms of quality of care and nurse workload, specifically biomechanical load.

This chapter addresses two research questions.

RQ 5 – *What are the biomechanical loads encountered by nurses while performing daily tasks in an inpatient unit and what are the time trace of the biomechanical loads for these nursing care task over a full shift, using a combination of DES and DHM?*

RQ6 – *How do changes in patient acuity, geographical patient-bed assignment and nurse-patient ratio affect the biomechanical loading in nurses and other indicators of nurse and patient outcomes?*

6.0 Methods

6.1 Model Creation

The DES model was created using ARENA (Rockwell). As illustrated in Figure 16, inputs to model include: 1) patient care data; 2) nursing care action postures; 3) hand forces; 4) physical layout; and 5) operating logic. 'Nursing care action postures' and 'hand forces' were used as inputs to the DHM model that created 'physical workload', which was programmed into the DES model along with 'patient care data', 'physical layout' and 'operating logic'. These are explained below.

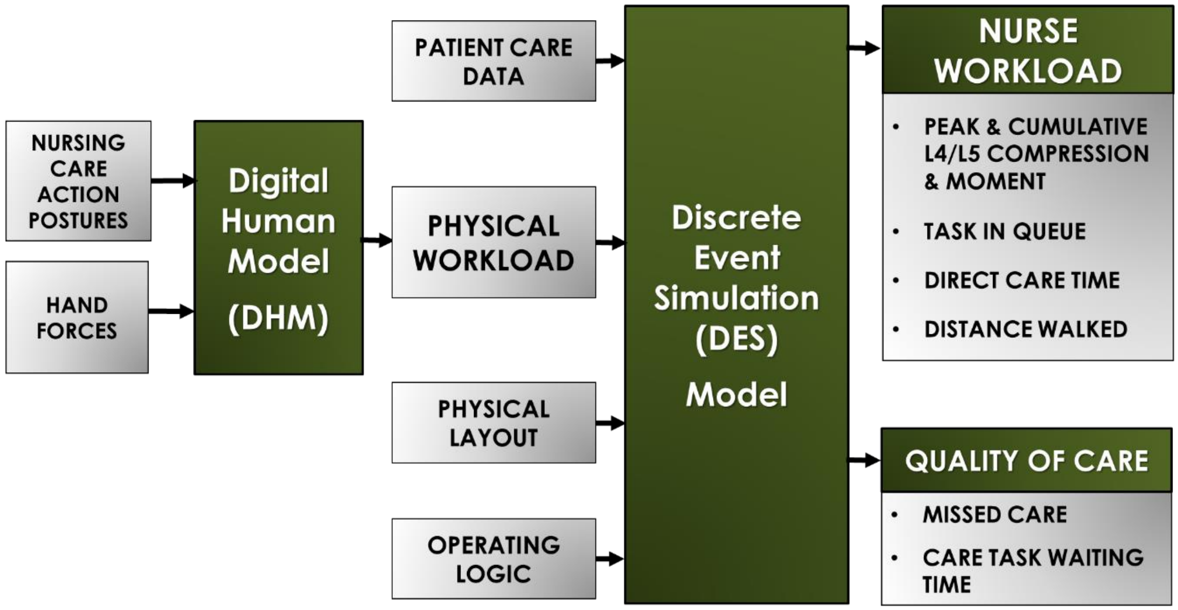

Figure 16 illustrates the block diagram showing how DHM and DES modeling capabilities are combined

6.1.1 Model Inputs

Patient Care data – Data was collected from a medical-surgical unit of a teaching hospital in Toronto, Canada, as part of cost center report called Infor, more commonly known as GRASP. GRASP data is entered manually by nurses at the end of the shift and contains information pertaining to the care that was delivered to the patient such as: task name, task group, task frequency and standardized task duration. A frequency weighted time average of the standardized GRASP time for each task to estimate the task duration. For acuity sensitive tasks, task duration is the sum of the frequency weighted time average and, the product of percent increase/decrease of patient acuity and frequency weighted time average. GRASP is a validated tool that uses a personal fatigue delay function (Farrington et al., 2000). The quality of a GRASP dataset is contingent upon the compliance level. For this research, the average compliance rate was 86% (Range: 78% to 97%). A dataset above 70% is to be considered to be of good quality. Patient care data was taken for a period of one year to account for the variations in healthcare demands.

Nursing care action postures and hand forces –These were obtained by means of a video recording study using the method of Norman et al. (1998). A registered nurse (RN) with 8+ years of medical-surgical unit experience was recruited to mimic the nursing care task postures. The participant demonstrated care task postures for the tasks as listed in the GRASP report. Hand forces were recorded via force gauge. Each care task posture was modelled in 4DWATBAK (University of Waterloo), DHM software. The 4D-WATBAK software allows the user to model the worker 'virtually' in work situations for multiple actions, and by accounting for the amount of time the worker spends performing each action. In this chapter, the 4DWATBAK software was used to determine physical workload in the form of L4/L5 compression load and L4/L5 moment. The DES model runs at the task group level. 4DWATBAK model provides biomechanical load at the action level. Therefore, a series of conversions were done to get the biomechanical load from a care task action level to a care task group level needed for input into the DES model. This conversion happened in two steps: 1) Conversion of biomechanical load from the '*action-level*' to the '*task level*', using an *exposure* time weighted average of the L4/L5 compression and moment for all the actions of a care task. 2) Conversion of biomechanical load from the '*task level*' to '*task-group level*', using a *frequency* weighted average of the L4/L5 compression and moment for each care-task in a care task-group.

The L4/L5 moment and compression of task groups bearing the highest load are considered peak. The biomechanical loads for all task groups were programmed into the DES model to estimate cumulative L4/L5 moment and compression for the shift. The simulant-nurse was modeled on the anthropometric measures of participant.

Physical layout – The physical dimensions of the selected medical-surgical unit were measured using Laser Measure GLM 100ft (Bosch). These dimensions were modeled using Visio (Microsoft) to create a 'virtual' layout of the unit in the DES model.

Operating logic consisted of 'care task priority rank', 'care-delivery logic', 'care task scheduling type' and 'nurse walking patterns'. These were obtained by means of a unanimous approach during focus group sessions with 15 RNs with two to 23 years of experience. 'Care task priority rank' illustrates which care tasks have increased priority over others (see Priority level information in Table 13). 'Care delivery logic' stated delivering the highest priority care task at the shortest distance. For 'care task scheduling type', all care tasks are programmed to happen randomly with exception of 'admission' (11am), 'nutrition' (7:30am, 12pm, 5pm), and 'hygiene' (8am).

Table 13 illustrates the care task programmed in this study along with 'Care task scheduling type', 'Time duration' and 'Care task priority rank', where 1 = Highest and 9 = Lowest

Care Task Group	Priority level (rank)	Care Task Scheduling type	Acuity Sensitive?		Time Duration (min)
			Time Duration	*Task Frequency*	
Assessment and Planning	1	Random intervals	-	-	2.58
Vital Signs	1	Random intervals		✓	1.58
Admission	2	Random intervals	-	-	16.05
Medication	3	Random intervals	✓	-	15.03
Vascular Access	4	Random intervals	-	✓	6.65
Activity	4	Random intervals	✓	✓	35.38
Treatments	5	Random intervals	✓	✓	5.7
Nutrition	5	Random intervals & Scheduled intervals (8AM, 12PM, 5PM)	-	-	8.62
Consultation	6	Random intervals	-	-	5
Hygiene	6	Random intervals + Scheduled interval (8:00AM)	-	-	10.27
Elimination	6	Random intervals	-	-	9.73
Discharge	7	Random intervals	-	-	10.7
Evaluation	7	Random intervals	✓	✓	3
Teaching and Emotional Support	7	Random intervals	✓	✓	20.89
Other Direct Nursing Care	8	Random intervals	✓	✓	14.54
Non-patient care	9	Random intervals	-	-	7.1

6.1.2 Model Outputs

The combination of DHM and DES modelling capabilities allowed quantitative estimates of the indicators for nurse workload and quality of care to be produced.

Nurse workload indicators:

'*Peak and cumulative L4/5 compression load and moment'* represent the highest load achieved for a task group (peak), while cumulative load entails the total load for each care task for the shift. *'Tasks in queue' is* a mental workload indicator (Potter et al., 2009). It represents the 'stack' of care tasks to be performed by the nurse at any given point of the shift. *'Direct care time*' represents the value-added time. It is the time spent by the simulant-nurse while delivering care. *'Distance walked'* entails the cumulative distance walked by the simulant-nurse for a shift.

Quality of care indicators:

'*Care task waiting time'* indicates the time a care task must wait in the queue before it is performed by the simulant-nurse. '*Missed care'* represents care tasks that are not performed before the end of the shift.

6.2 Demonstrator Case

To illustrate the modeling capability, experiments exploring the impacts of the following technical design and operational polices were explored: 1) geographical patient bed assignment, 2) patient acuity, 3) nurse-patient ratio.

The Baseline case – The DES model was run on baseline patient acuity data from GRASP with a nurse-patient ratio of 1:5, a standard for most patient care units (Aiken et al., 2001). The geographical patient bed assignment was 22meters, which was the most common patient bed-assignment for 10 RNs during in-person interviews

Experiment 1 – Geographical Patient-bed assignment

Geographical-patient bed assignment was operationalized as the average distance between the nurse station and patient beds (BND). As illustrated in Table 14, this experiment tested geographical-patient bed assignments as: 19, 26, 28 and 35 meters. The nurse-patient ratio was set at 1:5 and the baseline patient acuity data was taken from GRASP.

Experiment 2 – Patient Acuity

Patient acuity was operationalized as a function of care task duration and care task frequency for tasks. When the patient acuity is increased/decreased, a few care tasks have changes in their task frequency and/or task duration. Table 13 illustrates a list of acuity sensitive tasks. These were determined using a consensus approach in the focus group session. As illustrated in Table 14, this experiment tested patient acuity at the following levels: Baseline case, -5%, +5% and +10% of the baseline case, where, the nurse-patient ratio was 1:5 and geographical patient bed assignment was 22meters.

Experiment 3 – Nurse-patient ratio

Nurse-patient ratio refers to the number of patients assigned to one nurse. As illustrated in Table 14, the following conditions of nurse-patient ratio were tested: 1 nurse assigned to 2, 3, 4, 5, 6 patients respectively. The geographical patient bed assignment was set at 22meters and the baseline patient acuity data was taken from GRASP as in the other experiments.

Table 14 illustrates the experimental designs for this study

Experiment 1	**Experiment 2**	**Experiment 3**
Patient Acuity (%)	*Geographical Patient Bed Assignment (m)*	*Nurse-Patient ratio (nurse: patient)*
-5%	22	1:2
Baseline case	26	1:3
5%	28	1:4
10%	36	1:5 (baseline case)
-	-	1:6

The DES model was run for a period of 365 shifts calculated using Banks et al., (2005). To reach the optimal modeling state, a model warm up time of 61 shifts was used as per Welch's method (Hoad et al., 2008). The model was run for 12 hours to represent a typical day shift. To determine statistical significance, a one-way ANOVA with Post Hoc Test (Tukey's) was performed.

6.3 Results

By making a combined use of DHM and DES modelling capabilities, the cumulative L4/L5 compression and moment were successfully quantified along with their subsequent quality of care indicators. Figure 17 illustrates a time-trace graph for L4/L5 moment for the baseline case.

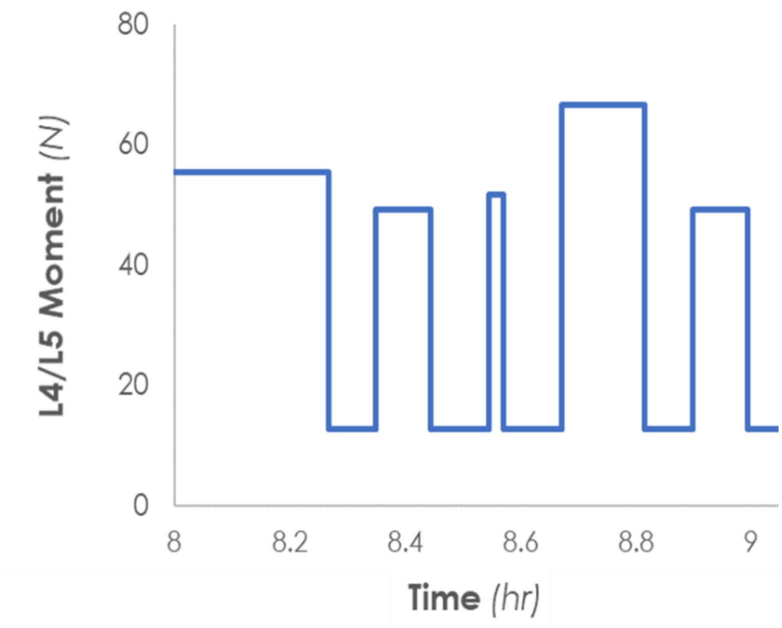

Figure 17 represents the time-trace graph for the L4/L5 moment from 8am to 9am for the baseline case

Table 15 illustrates the peak L4/L5 moment and compression load for the baseline case. The highest 'Peak L4/L5 moment and compression load' was for the task group 'activity', 112Nm and 3575Nm respectively. At the action level, the highest peak L4/L5 compression load was 6263N for 'lift patient head to wash back of the head' during all bathing tasks for the task group 'hygiene'. Followed by 'lift patient from bed', 3625N, for task group 'activity'.

Table 15 illustrates the Peak L4/L5 moment and compression load for the care tasks programmed in the simulation model

Task Group	**Peak L4/L5 Moment (Nm)**	**Peak L4-L5 Compression (N)**
Activity *(patient lifting tasks, such as: transfer patient to stretcher)*	112	3575
Admission	55	2673
Assessment and Planning	28	2223
Constant Observation	55	2673
Consultation	55	2673
Discharge	35	2341
Elimination	90	3195
Evaluation	17	1716
Hygiene	78	2941
Medication	51	2588
Non-Patient Care	76	2952
Nutrition	67	2840
Other Direct Nursing Care	57	2694
Teaching and Emotional Support	21	2121
Treatments	49	2570
Vascular Access	66	2830
Vital Signs	52	2625

The baseline case resulted in a ‘cumulative L4/L5 moment’ of 13.78 MNms, a ‘cumulative L4/L5 compression load’ of 23.85 MNs, with an average ‘task in queue’ of 20 tasks and a ‘distance walked’ of 11.42 km. In addition, a ‘care delivery time’ of 11.56 hour with a ‘care task waiting time’ of 0.94 hours led to the ‘missed care’ of 27 tasks.

6.3.1 Experiment 1: Geographical-based Patient-Bed Assignment Results

Table 16 shows the detailed results of the outputs in response to bed assignment changes. For nurse workload indicators, the ‘cumulative L4/L5 compression load’ ranged from 22.76 to 24.95 MNs, where the average number of ‘tasks in queue’ had a range of 20 to 21 tasks. The ‘distance walked' spanned a range of 11.42 to 13 km. For the quality of care indicators, the 'care task waiting time' of 0.94 to 1 hour was observed where 'missed care' tasks were 27 to 34.5 tasks. Figure 18 represents the relation between the percentage difference from the baseline case of 'cumulative L4/L5 compression load' and 'distance walked'.

*Table 16 illustrate the results for Experiment 1: Geographical-based Patient-bed assignment. * represents baseline case (22m)*

Geographical Bed Assignment	**Nurse Workload Indicators**				**Quality of Care Indicators**	
	Cumulative L4/L5 compression load	*Tasks in Queue*	*Distance walked*	*Direct Care time*	*Missed care*	*Care task waiting time*
(m)	*MNs (Δ% base)*	*tasks (Δ% base)*	*km (Δ% base)*	*hr (Δ% base)*	*tasks (Δ% base)*	*hr (Δ% base)*
22*	24.95 (0%)	20 (0%)	11.42 (0%)	10.56 (0%)	27 (0%)	0.94 (0%)
26	24.6 (-1.4%)	20.5 (3%)	11.72 (3%)	10.35 (-2%)	30 (8%)	0.96 (2%)
28	23.85 (-4.4%)	20.5 (3%)	12.28 (10%)	10.33 (-2%)	30 (8%)	0.96 (2%)
36	22.76 (-8.8%)	21 (7%)	13 (16%)	9.81 (-7%)	34.5 (20%)	1 (5%)

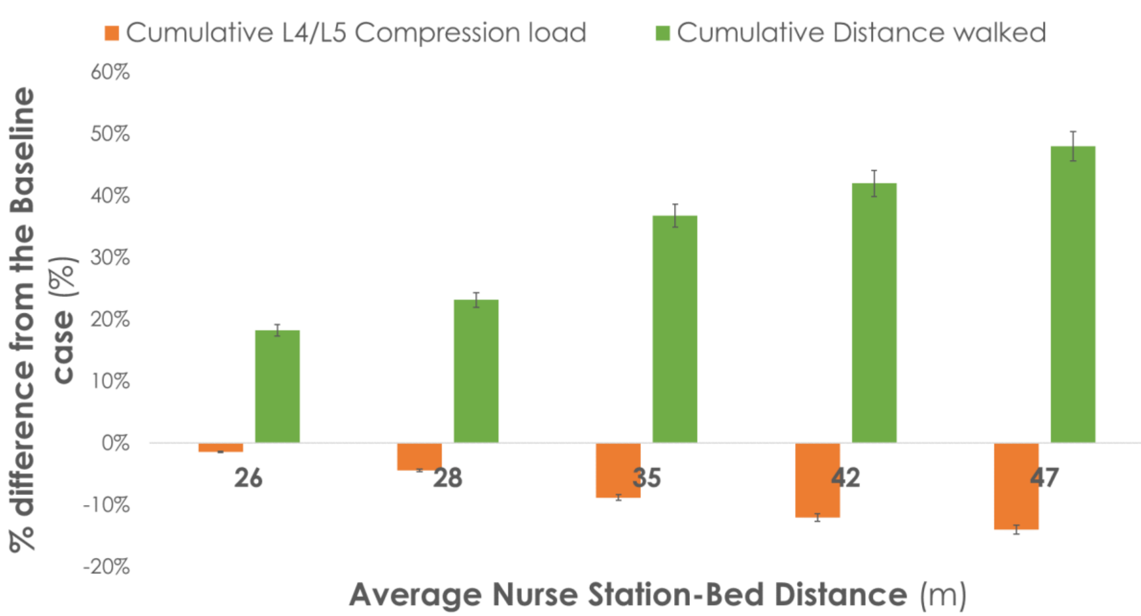

Figure 18 illustrates the percentage difference from the baseline case of 'cumulative L4/L5 compression load' and 'distance walked'. Where, the error bars represent the standard deviation

6.3.2 Experiment 2: Patient Acuity results

Table 17 shows the detailed results of the outputs in response to different patient acuity levels. Focusing on nurse workload indicators, a range of 'cumulative L4/L5 moment' of 13.6 to 14.78 MNms was observed, where the average number of 'tasks in queue' had a range of 11 to 23 tasks. The 'distance walked' spanned a range of 11.02 to 12.95 km. Regarding quality of care indicators, a 'care task waiting time' of 0.89 to 1.05 hour was observed where 'missed care' tasks were 13 to 32 tasks. Figure 19 represents the relationship between the percentage difference from the baseline case of 'cumulative L4/L5 moment' and 'distance walked'.

Table 17 illustrate the results for Experiment 2: Patient acuity

Patient Acuity	**Nurse Workload Indicators**				**Quality of Care Indicators**	
	Cumulative L4/L5 moment	*Tasks in Queue*	*Distance walked*	*Direct Care time*	*Missed care*	*Care task waiting time*
	MNms (Δ% base)	*tasks (Δ% base)*	*km (Δ% base)*	*hr (Δ% base)*	*tasks (Δ% base)*	*hr (Δ% base)*
-5%	14.78 (7%)	11 (-44%)	11.02 (-4%)	11.06 (-2%)	13 (-52%)	0.89 (-4%)
Baseline case	13.78 (0%)	20 (0%)	11.42 (0%)	11.25 (0%)	27 (0%)	0.94 (0%)
+5%	13.79 (0.05%)	21 (2%)	12.94 (13%)	11.49 (2%)	28 (4%)	0.95 (-1%)
+10%	13.16 (-4%)	23 (11%)	12.95 (13%)	11. 65 (3%)	32 (19%)	1.05 (0%)

6.3.3 Experiment 3: Nurse-patient ratio results

Table 18 shows the detailed results of the outputs in response to different nurse-patient ratios. A range of 'cumulative L4/L5 moment' of 11.47 to 13.8 MNms was observed with a 'cumulative L4/L5 compression loads of 21.58 to 23.91 MNs for nurse workload indicators. The 'distance walked' spanned a range of 5.26 to 13.08 km with a 'task in queue' range of 2 to 27 tasks. For the quality of care indicators, a range of 1 to 36 tasks were classified as 'missed care' with a 'care task waiting time' of 0.12 to 1.03 hours. Figure 20 represents a ceiling effect beyond which the loading did not increase for the 'cumulative L4/L5 compression load' and 'cumulative L4/L5 moment', while an increase for 'missed care' was also observed.

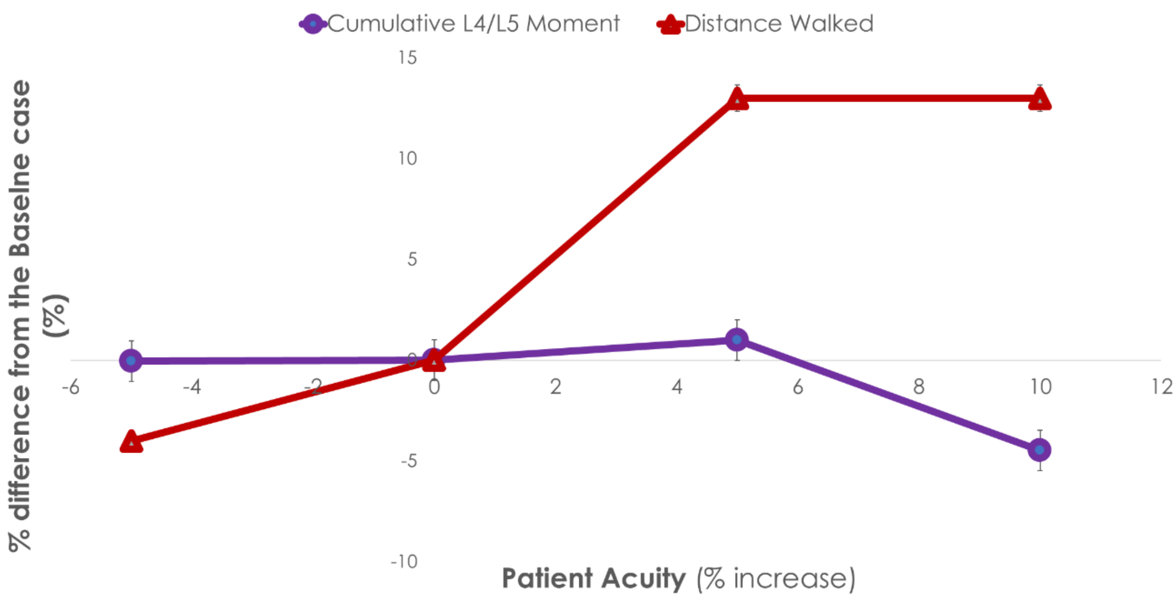

Figure 19 illustrates the percentage difference from the baseline case of 'cumulative L4/L5 moment' and 'distance walked'. Where, error bars represent standard deviation

Table 18 illustrate the results for Experiment 3: Nurse patient ratio. Where, 1 nurse assigned to 5 patients is the baseline case

Nurse-patient ratio	**Nurse Workload Indicators**					**Quality of Care Indicators**	
	Cumulative L4/L5 moment	*Cumulative L4/L5 Compression load*	*Tasks in Queue*	*Distance walked*	*Direct Care time*	*Missed care*	*Care task waiting time*
	MNms (Δ% base)	MNs (Δ% base)	tasks (Δ% base)	km (Δ% base)	hr (Δ% base)	tasks (Δ% base)	hr (Δ% base)
1:2	11.47 (-17%)	21.58 (-10%)	2 (-93%)	5.26 (-47%)	5.26 (-55%)	1 (-90%)	0.12 (-81%)
1:3	12.09 (-12%)	22.01 (-8%)	4 (-86%)	6.28 (-41%)	7.93 (-32%)	3 (-79%)	0.31 (-63%)
1:4	13.75 (0%)	23.78 (0%)	9 (-56%)	10.26 (-10%)	10.83 (-7%)	18 (-29%)	0.87 (-7%)
1:5	13.78 (0%)	23.85 (0%)	20 (0%)	11.42 (0%)	11.56 (0%)	27 (0%)	0.94 (0%)
1:6	13.8 (0%)	23.91 (0%)	27 (35%)	13.08 (9%)	11.65 (1%)	36 (29%)	1.03 (9%)

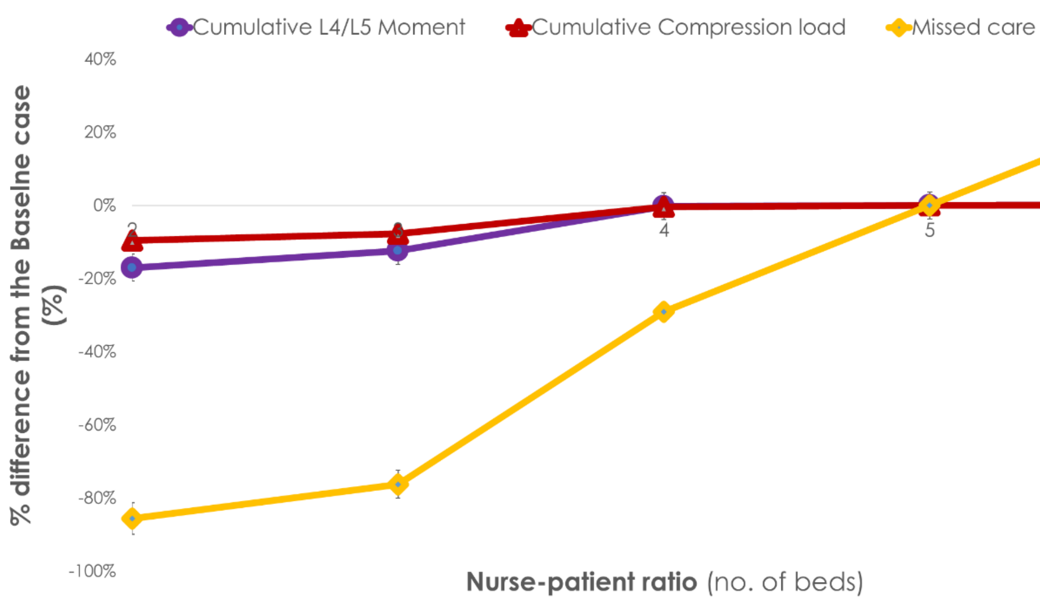

Figure 20 represents a saturation effect for the biomechanical load 'cumulative L4/L5 compression load' and 'cumulative L4/L5 moment', while a linear increase for 'missed care' is observed. Where, error bars represent standard deviation

A one-way ANOVA showed significant statistical difference (p<0.005) for all indicators with exception of '*distance walked*'. A Post Hoc (Tukey's test) showed a statistically significant difference for '*cumulative L4/L5 moment*' for cases: -5% and 5% of baseline case, -5% and 10% of baseline case, 'baseline case and 10% of baseline case', '1:2' & '1:4'. For '*tasks in queue*', '*care delivery times* and '*missed care*', -5% of baseline case and baseline case, -5% & +5% of baseline case, -5% & 10% of baseline case, '1:2' & '1:3', '1:3' & '1:5', '1:3' & '1:6', '1:4' & '1:6', '1:2' & '1:6', and '22m' & '36m', a statistically significant difference was observed. For '*care task wait time*', a statistically significant difference was observed for only the baseline case and -5% of the baseline case, baseline case and 5% of the baseline case and -5% and10% of the baseline case, '1:2' & '1:5', '1:2' & '1:6', '1:3' & '1:6', and '22m' & '36m'.

6.4 Discussion

In this chapter, a novel methodological approach that integrates biomechanical modelling (DHM) with flow simulation (DES) in a healthcare environment was successfully developed. In the past, this was only done in manufacturing (Dode et al., 2016; Dode, 2012; Kazmierczak et al., 2007). While stand alone DHM methodologies have existed before but these methodologies have had difficulty in predicting the time history i.e. the sequence of tasks performed (Wells et al., 2007).

By combining DHM and DES, we make an advancement are in healthcare as DES provides the sequence (time history) of care tasks performed and DHM can be used to provide the biomechanical load. This approach can yield time-sequence and work patterns for a nursing shift. Nursing is a high-risk sector for MSD (Bernard, 1997). This knowledge can help to better manage MSD risk, which is difficult to achieve with stand-alone biomechanical modelling or observational risk assessment tools. As a demonstrator case, this chapter tested the impact of changing technical design and operational policies, including, geographical patient-bed assignment, patient acuity and nurse-patient ratios.

6.4.1 General simulation results

It is a challenge to estimate the threshold value for cumulative L4/L5 loading (Fischer, Albert, McClellan, & Callaghan, 2007). In the most expensive lower back pain study by Norman et al. (1998), they quantified the cumulative L4/L5 loading for workers without lower back pain reports as 19.5 MNs and workers with lower back pain as 21.0MNs. The simulation model showed the cumulative L4/L5 compression load for shift-long nursing work as 23.85MNs, which is greater than load for automotive workers with lower back pain. The shift length for the automotive workers in the study by Norman et al. (1998) was 8 hours, a standard in manufacturing. The shift length for the DES model for nurses was 12 hours, which is the standard shift-length for nurses (Garrett, 2008). Which explains this increase in biomechanical loading. This provides evidence that 12-hour shifts for nurses contributes to increased MSD risk. At the action level, the highest 'peak L4/L5 compression load' was for the action 'Lift patient head and wash head' of 6263 N, belonging to the 'hygiene' task group. This action exceeded NIOSH action limit 3433 N and NIOSH maximum permissible limit 6376 N (Neumann et al., 1999). The second highest 'peak L4/L5 compression load' was for the action 'patient lifting' action for task 'up in chair', 'ambulation', 'patient turning' that consisted of 3625N that were part of the task group 'activity'. This action only exceeded the NIOSH Action limit 3433N (Neumann et al., 1999). Even though the highest MSD risk action for the peak biomechanical load belonged to the task group 'hygiene', the simulation model shows the task group 'activity' as the highest MSD risk at the task group level. This is because the biomechanical load calculation was done using a frequency-exposure time weighted average, where the time duration for the 'lift patient head and wash head' action of the 'hygiene' task group, was 12 seconds. This only happens for two care tasks 'bathing' and 'post op' bathing. These care task happen less frequently in-comparison to other tasks 'hygiene tasks'. However, the 'patient lifting' action for task group 'activity' happens for three different tasks 'up in chairs, 'ambulation' and 'patient turning'. Where, each care task happens more frequently in-comparison to the other 'activity' care tasks and each action takes longer. Hence, the reason why the care task group 'activity' has more MSD risk in-comparison to 'hygiene'. This modelling approach quantified the biomechanical load for nurses working in a medical-surgical unit. Some of the patient handling care tasks in medical-surgical unit are similar to those in long-term care. The peak load for these tasks were found in a similar range by Holmes et al., (2010) who studied the biomechanical loads for long-term care nurses.

Butt et al., (2004) reports that nurses walk an average of 10.86km in a 12-hour shift. The DES model reported similar findings where the simulant-nurse walked an average of 10.66km (SD = 0.9) for a 12-hour shift across all conditions. The slight increase (1.8%) in the distance walked reported by *Butt et al.,* (2004) can be attributed to different patient acuity levels for patients in the unit, and changes in unit layout.

Hendrich et al., (2008) conducted a time and motion study in 36 hospitals to quantify how nurses are spending their time. Nurses spend 77.7% of their time in delivering care. The DES model reported similar results where that simulant nurse spent 78.6% of its time in delivering care. When the nurse was assigned to patient beds further from each other and the nurse station, all indicators of nurse workload increased, and quality of care decreased.

6.4.2 Experiment 1: Geographical patient-bed assignment results

This experiment provided this unique insight: As the patient-beds were assigned further away from the center of the unit, the simulant-nurse spent reduced time delivering care and relatively more time walking. Since the L4/L5 compression load of walking is less than the compression load of care tasks, the compression load of a nurse assigned patient-beds closer to the nurse station was higher (24.886MNs, BND = 26m). In comparison, a nurse assigned to patient beds further from one another and the nurse station spends more time walking and less time delivering care. Thus, lowering the cumulative compression (22.76MNs, BND = 36m) as the spine load in walking is lower than in most care delivery tasks. Therefore, when BND is greater, the simulant-nurse walked more, and relatively less care tasks were performed that led to relatively less cumulative L4/L5 compression load. There seems to be a trade-off, as the MSD risk seems to be reduced when the nurses are assigned to beds away from the center of the unit, but the quality of care deteriorated.

6.4.3 *Experiment 2: Patient acuity results*

When the simulant-nurse was assigned to more acute patients, the time duration of most care tasks increased along with their frequency. At the task group level, proportion of 'L4/L5 moment' of non-acuity sensitive tasks (479Nms) was much higher than acuity sensitive tasks (428Nms). Most missed care tasks belong to non-acuity sensitive tasks. Therefore, the cumulative L4/L5 moment slightly decreased (-4%) for 10% increase in patient acuity. In addition, the walking distance for the simulant-nurse also increases (up to 13%) as the simulant-nurse had less idle time and now spent more time delivering care (+3%). There seems to be a trade-off, as the MSD risk seems to be reduced when the nurses attend to more acute patients but the quality of care is deteriorated.

6.4.4 *Experiment 3: Nurse-patient ratio results*

When the simulant-nurse was assigned to more patients, the average number of 'tasks in queue' increased by up to 35%. Since the simulant-nurse was working near full capacity with a 'direct care time' of 11.56 hours for the baseline case, this additional workload led to a 'missed care' of up to 29% as the 'care task waiting time' increased by 9% and up to a 35% increase in 'task in queue' was observed. A 'saturation effect' can be observed for cumulative L4/L5 moment and compression load as the simulant nurse does not have the time capacity to attend to this extra demand for care. Similar to the above experiments, there seems to be a trade-off, as a 'saturation effect can be observed for MSD risk when attending to more patients while, the quality of care is deteriorated.

For all three experiments, trade-offs can be observed between MSD risk and quality of care. These trade-offs can easily be tested and quantified using this simulation approach, to inform policy decisions that addresses the needs of both nurses and patients.

6.4.5 *Implications for the Healthcare industry*

The approach developed in this research can provide an evidence-based evaluation of potential changes to the healthcare system design by proactively quantifying biomechanical load, nurse workload and quality of care under different system design parameters. This modeling methodology may be used to proactively test ‘single action’ improvement studies without the risk of trial and error. In addition, this methodology can be used by *design engineers*, to better design products, such as patient lifting devices. Most patient-lifting devices are not used by nurses because these take more time and are not easy to handle (Kucera et al., 2019). This modelling capability can be used to provide quantifiable measures about the impact of improved usability of these devices, through decreased time requirements and their effect on ‘missed care’, ‘care task waiting time’ and biomechanical loads. *Ergonomists* could measure the system performance (nurse and patient outcomes) and health of workers (MSD risk). *Architects* could apply this modelling approach to better design and test unit layouts that support safe biomechanical loads and the quality of care. *Charge nurses* could use these this data to find optimal patient-bed assignment. *Administrators* could test policy solutions to identify options that would better meet the needs of nurses while supporting the quality of care for patients. This modelling approach should now be tested with these potential users to understand how to best build and apply such models to support their decision-making efforts. Further research on this needed

MSD risk is not only contingent on biomechanical load. It is impacted by the extensive work demand of the worker (in this case the nurse). These have implications on psychosocial aspects as well. This research quantified the increasingly steady high demands of nursing work. Kramer & Schmalenberg, (2008) have reported nurse to have low to moderate autonomy in their work. The Karasek’s ‘Demand Control’ model (1979) can be used to understand this. The Karasek’s model categorizes these low-moderate autonomy jobs with high work demand as ‘high strain jobs’. In the absence of steps to improve nurses sense of job control, increased job demands will tend to shift nurses towards a ‘high strain’ situation, thereby increasing their risks of work-related injury and illness (Gingras et al., 2010; Karasek, 1979; Rizo-Baeza et al., 2018). Further research on the psychosocial implications of such modelling results are required. This simulation approach can be used to better understand this relation. However, further testing is required.

6.4.6 Methodological Modelling Limitations

Model granularity issues– The DES modeling capability operates at the ‘task group’ level whereas the DHM model quantifies biomechanical load at the ‘action’ level. Therefore, conversions were made using frequency and exposure time weighted averages to calculate biomechanical loads. One of the trade-offs of modeling at the task group levels is that the model was not able to fully illustrate peak biomechanical load for a less frequent action with reduced exposure time. It is possible to have the DES modelling capability operate at the action level but there is a trade-off. The simulation run time and modeling time and post-simulation data analysis time will increase making simulation potentially less desirable to the stakeholders. Having said that, this modelling capability can be extended to reflect peak and cumulative biomechanical load at the action level.

Anthropometric issues –The simulant-nurse was modeled on the anthropometric measures of the study participant. This modelling approach can easily be adapted to different anthropometric measures. Further research is required to quantify the impact of changing the anthropometric measures of nurse in terms of biomechanical load and quality of care.

Adaptability issues – The demonstrator model is a representation of a medical-surgical unit and there may be differences in the care tasks between different units (example: emergent care or neurological unit) but this modelling capability can be easily adapted to different units.

Future work – Next steps in model development include measures of fatigue dose and fatigue recovery time along with error rates. These outputs could help administrators understand and predict changes on a much broader scale regarding nursing workload and its relation to the quality of care.

6.5 Conclusion

In this chapter, a novel methodology was developed that integrated biomechanical modelling (DHM) with flow simulation (DES) in a healthcare setting to quantify biomechanical loading and quality of care in nursing work. As a demonstrator case, variations in geographical patient bed assignments, patient acuity and nurse-patient ratios were tested. Each experiment provided unique insights. 1) Greater distance walked for nurses lead to reduced biomechanical load and less care is delivered. As the biomechanical load for walking is much less than biomechanical load of care tasks. 2) When nurses are assigned to more acute patients, a decrease in L4/L5 moment is observed (4%) as the task duration and frequency of most care task increase. Due to increased care demands, nurses must now spend more time delivering care. Since the care demands are much higher than the current capability of nurses, quality of care is deteriorated (increased missed care). 3) When nurses are assigned to more patients, a 'ceiling' effect on biomechanical load can be observed as nurses do not have the time to attend to this extra demand for care. the biomechanical load (compression and moment), increases by 17% and 10%

respectively. This modelling approach allows for prospective ergonomics from readily available data to predict biomechanical and injury loading for nurses.

6.6 Ethics approval

The study was approved by the *Ryerson Research Ethics Board (REB # 2017-340)* and *University Health Network's REB Coordinated Approval Process for Clinical Research* (*CAPCR # 17-6084)*.

CHAPTER 7

DISCUSSION

This chapter refers back to the primary RQ presented in Chapter 1 (p.23) – *How can the effects of changing technical design and operational policy parameters on nurse and patient outcomes, be quantified using human factors enabled discrete event simulation?,* and provides a general discussion of the entire thesis. Following discussion of each research question is a review of the contributions of this thesis. The chapter ends with a discussion of the limitations of this research and future work.

7.1 General Overview

This research addresses the need to focus on HCPs to improve the healthcare system, as outlined in the editorial of the special issue of IISE Transactions in Occupational Ergonomics and Human Factors (Neumann et al., 2018). HCPs are central to healthcare system and the quality of care that gets delivered to the patients. In addition, this multidisciplinary research serves as a response to the need for a tool that can better manage the work demands and workload of nurses (National Advisory Group on the Safety of Patients in England, 2013). The need was addressed by successfully creating a human factor enabled nurse-focused computerized 'flow' simulation (DES) model. The DES model provided quantifiable measures of the impact of changing technical design and operational change on nurse workload and the quality of care. While traditional approaches have been limited to modeling patients as a 'product flow' in a production system; this research modeled the process of care delivery by nurses. The overall result from these series of modeling experiments are that nurses are overworked, and they have more tasks than they can perform in a 12-hours shift. They are not able to finish care delivery tasks with the resources they are provided. Caruso, (2014) reports that overworked nurses are at an increased risk for deteriorated quality of care, neurocognitive functioning, injuries, obesity, and a range of chronic diseases. This study provides quantifiable evidence that the state of being overworked leads to increased missed care, increased care task waiting time, mental and physical workload.

In Figure 21 is an overview of the specific studies completed for this research program including how each technical design and operational policies were tested by a series of research questions (RQ). Detailed discussions are provided within each chapter.

7.2 RQ 1 – Pilot DES Model Creation and Demonstrator Case

In chapter 2 is an explanation of the development of a nurse-focused simulation approach that can quantify nurse workload and quality of care under different technical design and operational policies. As a demonstrator case, nurse-patient ratios were tested. High nurse-patient ratios, as an indicator of staffing levels, have had a direct link to poor quality patient care and adverse outcomes for the HCP Despite studies such as Aiken et al., (2001); Djukicet al., (2012); Heinen et al.,, (2013); Griffiths et al., (2018), have demonstrated the need for adequate staffing ratios, The National Institute for Health and Care Excellence (2014) concluded:

"Insufficient evidence is available about the relationship between staffing, ward-level factors and patient outcomes" (p32).

As illustrated in Figure 21, the creation of a DES demonstrator model provides a method for gathering quantifiable evidence that can show the relationship between nurse-patient ratios and ward-level outcomes such as the quality of care (patient outcomes) and nurse workload (nurse outcomes).

7.3 RQ 2 – Pilot DES Model Extension: Patient Acuity and Nurse-Patient Ratio

Chapter 3 discusses the extension of the nurse-focused DES model where different workload factors were tested. Patient acuity and nurse-patient ratios are two of the significant drivers of quality and workload (Aiken et al., 2018; Aiken et al., 2008; Alghamdi, 2016; Hurst, 2018). Hospitalized patients are increasingly more ill while health resources are more limited. Newer polices to increase the patient throughput, by discharging patients earlier than before, have resulted in more acutely ill patients in the unit (Hughes, 2008). This led to the nurse attending to more acutely ill patients on the unit. The National Advisory Group on the Safety of Patients in England (2013) reported:

"indeed, higher acuity doubtless requires more generous staffing" (p23)

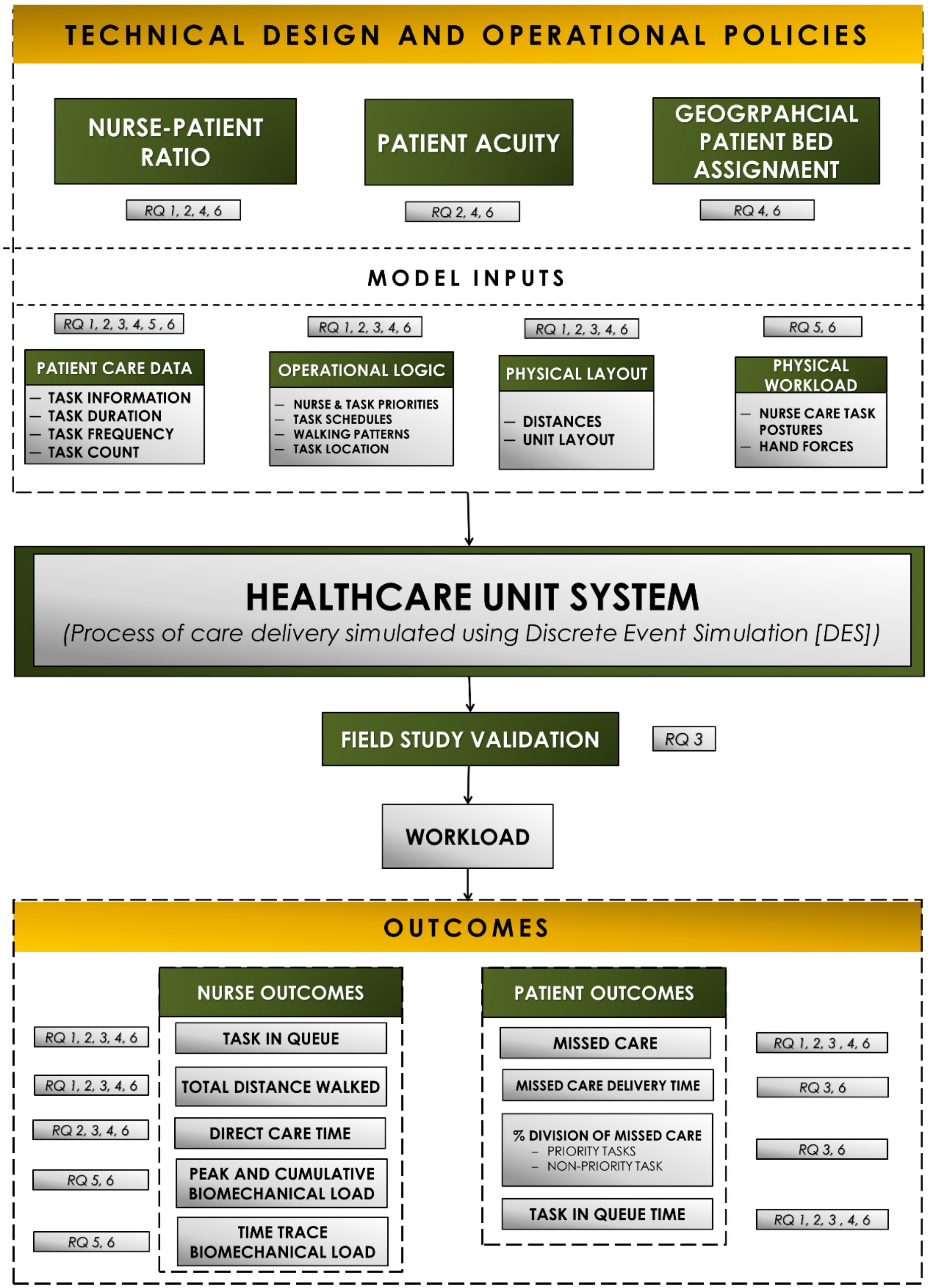

Figure 21 illustrates how a design orientated approach can address the needs of the healthcare professionals (HCP) and patients, by focusing on the health and workload of HCP(in this case, nurses), and the quality of care delivered to patients.

As illustrated in Figure 21, to answer RQ2, the interaction of patient acuity and nurse-patient ratios were quantified in terms of nurse workload and quality of care by means of a sensitivity analysis. This sensitivity analysis illustrated how incremental increases in patient acuity with the same nurse-patient ratio would increase nurse workload, and the quality of care incrementally deteriorated. More importantly, the results of this experiment addressed the National Advisory Group on the Safety of Patients in England (2013) need for a dynamic tool that can assess staffing levels (nurse-patient ratio) and patient acuity as a way to address workload and patient safety (quality of care).

The emphasis in Chapter 2 and 3 (RQ1 and 2) was on the development of an adaptable content sensitive method, rather than a definitive general answer to a specific scenario of interest to a stakeholder. To test the ability to simulate the process of care delivery using flow simulation (DES), the demonstrator model was created from different sources, such as, patient data was taken from a neurological unit; subject matter expert was from medical-surgical unit; unit layout was built from a hospital layout manual. Using data from different sources, may compromise the quality of modeling outputs.

7.4 RQ 3 – Model Validation via Field Study

After answering RQ 1 and 2, the research team presented these findings to the directors and managers of a metropolitan area teaching hospital in Toronto, Canada. While they appreciated the work, the need for an 'external' model validation was identified and subsequently tested in RQ3. Therefore, in chapter 4, the methodology used to create a valid nurse-focused simulation model that can quantify nurse workload and quality of care was described. The DES model was adapted to a medical-surgical unit of a metropolitan teaching area hospital as the largest proportion of acute care nurses work in a medical-surgical unit (Canadian Institute of Health Information, 2017). The outputs of the DES model were compared to real-world outcomes by means of a field study. Excellent consistency between modeling and real-world outcomes was demonstrated (ICC coefficient = 0.99, 0.99, 0.87, 0.85; Spearman ranked correlation coefficient = 0.78).The outcome of the study was validation of the nurse focused simulation model developed to quantify nurse workload and quality of care proactively. Future researchers can now use this technique to create valid models and run experiments to test the impact of different technical design and operational policies on nurse workload and quality of care.

The question about validity of simulation model has been debated but some simulation scholars have argued that validating each simulation model does not add value to the overall agenda of using simulation and modelling. This issue was addressed in Chapter 4 where it was shown that the simulation model can be validated at the midpoint without extensive external field validation studies. If the simulation model is created using appropriate data and 'internal' validation of the model is carried out then further validation is not needed. Using this approach to developing valid simulation model may avoid the need for excessive field validation. However, further research is required when the DES model is adapted to a different unit and the field outcomes are compared to the DES modelling outcomes. Detailed discussion of model validity is presented in the discussion of Chapter 4.

7.5 RQ 4 – Geographical-Patient Bed Assignment

RQ4 makes use of the validated model developed in Chapter 4 to address the need for using a patient bed assignment tool that is based on the unit geography (Cignarale, 2013; Goodman, 2017). As illustrated in Figure 21, RQ4 was focused on quantifying the effect of geographical patient-bed assignment on nurse workload and quality of care, by introducing variables 'inter-bed distance' and 'nurse station-bed distance'. By answering RQ4, future researchers can now use this research as a basis to test the efficiency of existing and/or new in-patient unit designs. Hospitals spend a lot of capital to design and construct new facilities. More capital is spent correcting the mistakes that were difficult to identify during the design phase. It is often not realistic to fix these mistakes such as the physical layout of the unit. For instance: once the building is made, it is very costly to change/remove load bearing beams of the building. This modelling technique provides proactive quantification of the potential impact of design on nursing workload and quality of care thereby allowing the user to test design alternatives which is a cheaper and safer approach to current trial and error methodologies. However, future research is needed to affirm this.

7.6 RQ 5 – Biomechanical Loading and MSD risk of Nurses

In chapter 6, the modeling capability was extended by incorporating the ability to quantify the biomechanical MSD risk for nurses. Nursing is a high-risk profession for MSD (Bernard, 1997; Pope et al., 1991; Trinkoff et al., 2003; Thinkhamrop et al., 2017). Quantifying the MSD risk opens doors to improve the physical well-being of nurses. This chapter combined the use of DHM and

DES to produce peak and cumulative biomechanical load over a full shift. Peak and cumulative load are well-known MSD risk factors for lower back pain (Norman et al., 1998). Future researchers now have a tool that can provide insight into the effect of improving the action of one or multiple care tasks over a full shift. RQ5 quantified these care task postures and provides a time-trace of biomechanical load. By providing a time-trace, hospital managers now have quantifiable data of the exposure time of biomechanical load that exceeded the NIOSH action limit and maximum permissible limit. Using this, hospital managers can now test other strategies to mitigate MSD risk such as hiring additional staff to cover peak load hours. Future researchers can use this research to test various devices designed to reduce MSD risk.

7.7 RQ6 – Biomechanical loading and MSD risk under different technical designs

As illustrated in Figure 21, RQ6 further tested this new modeling approach on nurse-patient ratio, patient acuity and geographical-patient bed assignment. Addressing RQ6 provided unique insights that 1) patients assigned to a bed away from the center of the unit led to a decreased biomechanical load, increased workload and deteriorated quality of care; 2) When nurses are assigned to more acute patients, a slight decrease in L4/L5 moment is observed as the task duration and frequency of most care task increase. Due to increased care demands, nurses must now spend more time delivering care. Since the care demands are much higher than the current capability of nurses, quality of care is deteriorated. 3) When nurses are assigned to more patients, a ‘ceiling’ effect on biomechanical load can be observed as nurses do not have the time to attend to this extra demand for care. Thus, quality of care deteriorates. Future researchers can now use this modeling tool to understand MSD risk for nurses attending to more acute patients or, when patients are assigned further away from the center of the unit, or, when assigned to more patients. The model is now ready for field testing where the design of nurse assistive devices can be tested in terms of nurse workload and quality of care. In addition, this model can now be used to quantify the impact of single-action improvement studies on full shift nursing work. For instance, in some units, catheters are placed at the most bottom cabinet in the clean utility room. This leads to additional bending for nurses. This model can provide quantifiable measures of whether improving the location of clean catheter bags may improve the cumulative biomechanical load of a nurse. Further research is required.

7.8 Contributions

This multidisciplinary research has the potential to shift healthcare system design and nurse workload management towards a more evidence-based use of quantitative indicators. As illustrated in Figure 22, this research extends the knowledge pool across multiple domains. Specifically, Industrial Engineering (IE), Healthcare (e.g. Nursing) and Human Factors.

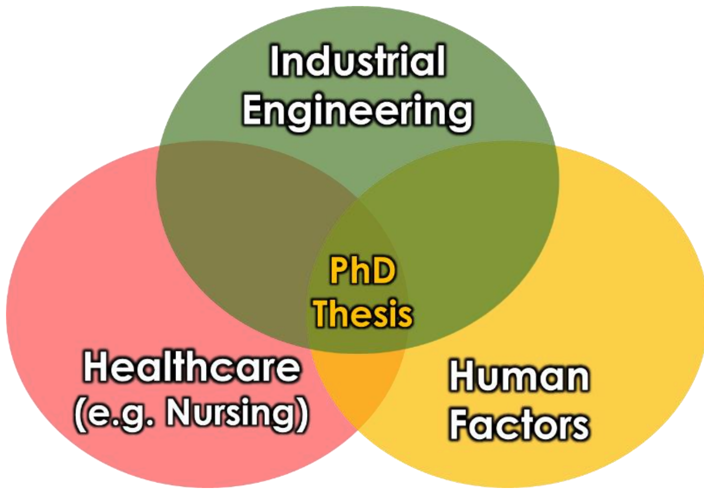

Figure 22 illustrates the scope of this multidisciplinary research conducted in this PhD thesis (Industrial Engineering; Healthcare, e.g. Nursing; Human Factors)

Following are the main contributions from this research.

1- Approach to Creating a Valid Human-Factors enabled DES Model

The biggest contribution of this thesis is developing a novel approach to creating valid HCP-focused DES model. Previously, healthcare flow simulation has been mainly used to model patients as a 'product' flow in a production system, despite the fact that nurses delivery 75% care in hospital settings (Nursing Task Force, 1999; Qureshi, Purdy, & Neumann, 2016). By developing this approach to creating valid nurse focused flow simulation models, we now have a capability to quantify nurse (workload) and patient outcomes (quality of care) under different technical design and operational policies. Validated modeling approaches are more credible and more desirable for the knowledge users and stakeholders as they provide more confidence in the data being used to support decision making. Using this modeling capability, future researchers can also create valid computerized flow simulation models. In addition, this adaptable modeling approach voids the need to constantly validate the simulation model for every design experiment.

Thereby, maintaining the overall cost-benefit of the simulation and modeling. However, this must be done with caution as the nursing care unit simulation model adapted to a home-care flow simulation model may require validation. Further research is needed to affirm this.

2- Quantifies Nurse Workload and Quality of Care

Due to the elusive nature of workload, quantifying nurse workload is a challenge (Arsenault Knudsen et al., 2018; Neumann et al., 2018). This doctoral research provides an approach to quantifying indicators of nurse workload and quality of care. The nurse focused modelling capability developed provides quantifiable proof that the current work demands (workload) can not be met by the nurse supported by the current technical support. This research can be used as tool to advocate for better working conditions and thereby improving quality of care. In addition, it provides the nursing unions concrete evidence to establish nurses being 'overworked' and its implications at a more systems-level.

3- Platform to test Technical Design and Operational Policies

Using this validated modelling approach, nursing leaders can proactively test the impact of newer policies and technical polices to quantify potential overtime at the unit level, and subsequent impact on quality of care. Quantifying work demands and nursing workload enables testing of strategies to better manage nurse workload that may subsequently reduce MSD risk, absenteeism and associated adverse outcomes. Reducing MSD risk for nurses can reduce the prospect of making errors such as mistakes, lapses and slip (Reason, 2004), thereby, improving delivery of care to patients.

This thesis quantified the increasingly high demands of nursing work. Which further provides explanation as to why an overtime of 20.1 million hours with an annual paid and unpaid cost of $968 million dollars in Canada was recorded in 2016, as compared to 19 million hours overtime in 2014 with an annual paid and unpaid cost of $860 million dollars (Canadian Federation of Nurses Unions, 2015, 2017a, 2017b). Demand has two aspects: physical and psychosocial. By quantifying the physical aspect of demand, this research can be used to understand the psychosocial aspect. Kramer & Schmalenberg, (2008) and Skår (2010) reported nurse to have low to moderate autonomy in their work. The Karasek's 'Demand Control' model (1979) categorizes these low-moderate autonomy jobs with high physical demand as 'high strain jobs'. In the absence of steps to improve nurses sense of job control, increased in job demands will tend to shift nurses towards a "high strain" situation (Gingras et al., 2010; Karasek, 1979; Rizo-Baeza et al., 2018), thereby increasing their risks of work-related injury and illness. This could explain why nursing to some is a 'deteriorating' profession (Heinen et al., 2013). If the current healthcare system does not change, a shortfall of 60,000 RNs can be expected by 2022 in Canada (Canadian Nurses Association, 2015), 1 million RNs in US by 2030 (American Association of Colleges of Nursing, 2019) and 7.1 RNs globally (World Health Organizaiton, 2016). However, further research on the psychosocial implications of such modelling results are required to affirm this.

4- Understanding of the relationships between design and operational polices, and nurse workload and quality of care.

The doctoral research provided a deeper understanding of the relationships between technical design and operational polices, and nurse workload and quality of care. This research provided quantifiable evidence for a directly proportional relationship between 'care task waiting time' and 'task in queue'. When there were more tasks in queue, the waiting time for care tasks increased. Similarly, greater number of 'tasks in queue' and 'direct care time' contributed to increased 'missed care' and 'missed care delivery time'.

While some relations might seem obvious, this research was able to provide insights to unique relationships. The biomechanical load (specifically, L4/L5 compression and momentum) reduces when the 'distance walked' increases. Since walking has reduced biomechanical load in comparison to care delivery tasks such as 'activity', 'elimination' or 'hygiene' etc. Increasing 'nurse-patient ratios' and 'patient acuity' levels lead to ceiling effect of biomechanical load. As nurses do not have the time to deliver further care tasks. As a result, the cumulative biomechanical load does not increase.

5- Tests the SEIPS 2.0 model

SEIPS 2.0 is a framework of representing the healthcare system that considers the outcomes of healthcare in two stances: HCP and patient outcomes. This thesis makes use of simulation technologies to model this framework and provide quantifiable effects of design and operational polices on HCP (nurse) and patient outcomes. In doing so, it provides a proactive stance for HCP focused improvement. These models integrate available evidence and data to help understand complex system dynamics that impact nurse and patient outcomes.

6 – Further established benefits of integrating Human Factors in Industrial Engineering

In the past, some engineers may have had differing attitudes towards human factors (Mekitiak, Greig, & Neumann, 2016). It maybe difficult to gain buy-in at the design and operational level. Some have even considered HF as a 'soft' science and have confined it to the realm of human resources (HR) only. On the contrary, the purpose of HF is to improve the overall wellbeing of the worker and improve system performance (International Ergonomics Association, 2018; Vicente, 2008). Incorporating HF in engineering methodologies has great benefits (Dode, 2012; Greig, 2016; Village, 2014). This research further provides evidence on how IE and HF, when combined, can assist in the improvement of worker (HCP) outcomes and quality (patient outcomes). By combining DHM in DES, design engineers and ergonomists can virtually test and qualify the biomechanical load of nursing work, thereby providing insight to MSD risk. This further addresses the need for a tool that can better manage MSD risk in nursing (Bernard, 1997; Bureau of Labor Statistics, 2011a).

7.9 Methodological Discussion

Modeling in-data– The modeling approach developed in this research uses GRASP as the primary source of patient care data. GRASP is a validated tool that uses standardized task duration with a personal fatigue delay of 7%. Similar to methods time management (MTM), it may be possible for some experienced nurses to complete tasks in less than the standardized task duration. Therefore, some results may be slightly inflated. As an alternative and/or when GRASP is not used by the organization to capture nurse workload, other data sources such as using the patient's electronic health record (EHR) may offer more reliable and precise data (Carayon et al., 2011). However, data availability might be an issue as not all hospitals use EHR.

In an interview with GRASP and Unit managers, it was pointed out that nurse work demands may vary throughout the year. For instance, motorcycle accidents increase in summer. Therefore, one year of GRASP data was taken for research experiments in Chapter 4 to 6. While taking an average of the entire year of GRASP data, the peak work demands in certain months could have been missed. The DES models were general representations of medical-surgical units for the whole year. Therefore, the certain peak or drop in work demands might have averaged out.

Model granularity – This doctoral research modeled the process of care delivery at the 'task group' level. Modeling at the 'task group' level led to using average performance expectations (GRASP).

While, simulating at the 'task' level is certainly possible but there is a trade-off that simulation run time will increase significantly while additional outcomes may be limited. While acquiring an expensive processor is certainly possible but the cost would need to be justified in terms of the return on investment. You can not expect a map of North America to reveal every bump in the road. Therefore, one must not let perfect be the enemy of good (Earle & Ganz, 2012). Research must be performed at the level of need i.e. is the task group level sufficient for testing the impact of system changes. Having said that, if the knowledge users' need this extra insight to the modeling outcomes, it is certainly possible as this nurse-focused DES modeling capability is quite adaptable.

Breaks and overtime – This thesis models a 12-hour shift with no breaks and does not model overtime. Therefore, the DES model maybe slightly over estimating nurse workload and quality of care. Breaks vary from hospitals to hospitals. In an interview with the Unit manager, it was pointed out that nurses are offered two 15-minute breaks and a half hour break for lunch. However, this is not the case for each unit. Some nurses prefer to take a cumulative one-hour break all together while nurses in others prefer two half hour breaks at different times. In future the model can be extended to include break time.

Day shifts –This DES modelling approach is a representation of day shifts. The DES model can be easily adapted to reflect night shift by providing the input patient care data for night shift patients. Care task frequency is reduced during night shift. However, and nurses operate at an increased the nurse-patient ratio.

Digital Human Modeling (DHM) – The demonstrator DHM model is a representation of a medical-surgical unit and there are likely differences in care tasks between different nursing units, for instance, emergency departments or critical care units. This modelling capability can be easily adapted to a different type of units. This study modeled a 95th percentile of male patients. In addition, the simulant-nurse was modeled on the anthropometry measures of the female nurse that participated in this research. While the range of the biomechanical loads across different technical design and operational polices may remain the same in these conditions, it is possible that anthropometric measures may differ for nurses of varying statures. The DHM model can be adapted to reflect this effect.

Variability – This research did not account for worst or best-case scenarios. The DHM models the most optimal state, where, patients were cooperative and were not resisting care. The DHM model could be adapted to provide accurate patterns of response to variability.

Externalities are real world phenomena that are complex and hard to simulate. These phenomena are often ignored by simulation scientists to balance the cost-benefit of the model. The conceptual model of this research was adapted from the SEIPS 2.0 model. The conceptual model has some externalities such as organizational culture, quality of leadership, equipment provided by the organization (lifting devices etc.) These were not modeled in this research. These externalities may have some impact on the reported outcomes of this research. Models are simpler representations of a complex system, taking all externalities into account may disrupt the cost-benefit of the model thereby defeating the overall purpose of simulation.

7.10 Future work

The product of this research is a tool for knowledge users, such as healthcare managers, to better manage the workload of HCP and improve the quality of care by modelling the impact of proposed technical design and operational policies. The next section provides details about how the DES modeling capability can be extended.

7.10.1 Extending the DES modeling capabilities

Newer outcomes – The DES modeling capability developed in this research needs interactive research methods where interviews, focus groups, surveys, dialogue and other participatory experiences (Laslett & Rapoport, 1975), can be used to see how the DES model can be adjusted or designed to better meet the needs of the decision-makers. This doctoral work can be extended to examine other outcomes to quantify *nurse discomfort, patient satisfaction, fatigue dose* and *recovery time, and error rates (slip, lapse and rework)* that might be impacted my workload demands.

Work Demands Variability – Since the work demands of nurse varies throughout the year (as per GRASP manager), it would be interesting to see the impact of *each month's GRASP data* in terms of nurse workload and quality of care. A possible future direction of this research could be to see variability in GRASP across the entire year.

Breaks and Overtime – The DES modeling approach can be extended to reflect multiple breaks for simulant-nurse and its subsequent effect on workload and quality of care. In addition, the DES model can be adapted to simulate overtime work.

Special conditions (Holiday season or Night shift) – This thesis modeled 'day' shifts only, which is quite different from 'night' and 'holiday shifts. During the night shift, the nurse may have to attend to more patients. Similarly, during the holiday' schedule, some personnel are not available, and nurses take on additional responsibilities. A future work of the simulation modeling approach developed in this research can be adapted to 'night' shifts and 'holiday' schedule.

Other Healthcare Settings – This research is now ready to be extended to other healthcare settings: home care, long term care, emergency clinic design, pharmacists, personal support workers and other health care professionals responsible for delivering patient care.

Future research work is now presented with a focus on other practice issues that could benefit from the use of DES modelling and also potential users of this modelling approach.

7.10.2 Potential Issues

While further testing is required, the following are some of the examples of potential research issues that that could be addressed using the products of this PhD thesis.

Issue 1 –During the field study of the selected patient care unit, the policy makers implemented the use of call phones to answer patient queries. While the initial premise was that this would lead to reduced walking, the policy makers did not consider the ramifications on the nurses' mental workload. The nurses received more frequent calls from their patients and most of these calls came during complex procedures where interruptions could have compromised the quality of care. This outcome could have been easily quantified proactively using the developed DES modelling approach. Therefore, this policy may have not been implemented nor would the hospital spend capital on expensive call phone system.

In addition, the same unit is now testing 'intentional rounds', which is unit-specific policy where nurses are required to visit patient rooms every hour, regardless of how many care tasks they have to do. This is just another example of 'trial and error' that could push nurses to unsafe and untested work environment conditions. Policies like this can easily be tested using the novel modelling capability developed in this thesis work. The DES model would provide proactive insight on the possible increase or decrease of mental workload (task in queue) and its subsequent impact of distance walked and missed care.

Issue 2 – During infection-related outbreaks like MRSA or E-coli etc., HCPs must wear protective gear that may extend the time duration for each care task to be delivered. The research developed in this PhD thesis can be used to quantify this delay proactively and calculate the effect on nurse workload and quality of care. The modeling capability developed in this thesis can be used to also establish optimal nurse-patient ratios that can improve quality of care and decrease nurse workload.

Issue 3 – A poor unit layout can decrease productivity, increase workload and impact the quality of care provided. The modelling approach developed in this is PhD thesis can be used to provide evidence regarding the impact of nurse-station facility design on quality of care and nurse workload (Luoma, 2006; Morelli, 2007; Reiling, Hughes, & Murphy, 2008) i.e. how would nurse workload decrease if the nurse-station is at the center of the unit or if there are two nurse-stations at the extreme ends of the unit. Some scientists have expressed concerns as this may increase physical and mental workload of nurses. This research can be extended to test and quantify the impact of adding two nurse-stations in the unit, in terms of nurse workload and quality of care.

Issue 4 – Nurses often attribute poor bed-assignment to their increase in workload. This research can be used to design the most optimal patient bed assignment for all nurses on the unit by providing quantifiable measures of the trade-offs between quality of care and nurse workload for each assignment option.

Issue 5 – During job shadowing, it was observed that the nurses use an automated medication dispensing machine to obtain medications for their patients. On a medical-surgical unit, pain management medications are used most frequently. These were placed in the lowest drawer of the machine. This led to additional bending that can create an increased MSD risk. A future extension of this project could be to re-arrange the medication location within the dispensing machine to quantity the effect on MSD risk, nurse workload and quality of care for shift-long work. Similarly, this research could be used to examine the impact when introducing new equipment such as patient handling assistive devices.

A good portion of nurse's work-related MSD risk and injuries can be attributed to patient lifting tasks. While extensive research has been done to develop tools that reduce this MSD risk; some aren't as popular amongst nurses as they are time consuming and difficult to move around. This research can be extended for product usability testing and their impact on quality of care, injuries and workload for full shift nursing work.

Issue 6 – This research can be used to explore different shift lengths in acute care. In the past years, there has been debate over the ideal shift length i.e. 8, 10 and 12 hour shifts (Garrett, 2008). This research maybe used to inform this debate by reporting the potential impacts on the quality of care and nursing workload.

Issue 7 – Newer technologies such as automating certain elements in healthcare system are on the verge of expanding in healthcare. Some healthcare managers are unsure about the investment to automate. The modelling capability developed in this research may be used to run experiments to gain proactive insight before extensive investment. For instance, during nurse job shadowing, it was observed that nurses sometimes had to make multiple visits to the clean utility room as some of the supplies were not available and they had to wait for stock to be replenished. This disrupted the quality of care delivered and further increased mental workload. Installing sensors may trigger automatic emails to the replenish personnel to only bring specific utilities that need replenishment. While this may seem obvious, managers would like to see how this would impact quality of care and HCP workload.

The next section discusses the potential users of this research and who would benefit from solving these issues.

7.10.3 Potential Users

There are several possible users of this research. Some are presented below. However, further research is required to understand how this research may help these users.

When a nurse falls ill and is absent from work, they are often replaced with a less experienced nurse that doesn't match patient requirements (National Institute for Health and Care Excellence, 2014). The DES model developed in this thesis can be used by **unit managers** to test and quantify this effect in terms of quality of care and nurse workload. In addition, solving issue # 1 and 2 are examples of how this modelling approach can assist unit managers with their daily planning.

The duties of a **charge-nurse** are complex. They have to take into account the sickness level of patient, the amount of care required and the location of patient bed when creating the bed assignment (Cignarale, 2013). Solving issue # 4 is an example of how this simulation model can assist charge-nurse.

Policymakers can design and test policies that cater to the needs of nurses. Solving issue # 1, 2 and 6 are examples of how simulation models can be used select newer policies that assist the HCP and improve quality of care. In this case, policy makers may be the vice presidents, directors, nurse managers and even government, professional associations or nursing unions such as CNFU (Canadian Federation of Nurses Unions), ONA (Ontario Nurses Association), Australian Nurses Federation etc. This research has been presented to the directors and unit managers at the hospital referred to in this study on multiple occasions. They have expressed interest in further development of this research and would like to use this research to gain insight into implementing unit-specific policies.

This adaptable modelling tool benefits **architects** by providing a support tool that can be used to better design the unit layout and floorplan. Solving issue # 3 is an example of how this thesis can assist architects. While there have been a few published studies that have tested unit layout , they have been limited to field observations (Hua et al., 2012; Seo, Choi, & Zimring, 2011; Yi & Seo, 2012). There remains a need for a tool that can 'virtually' quantify the impact of unit layout in terms of workload for nurses and quality of care. This modelling approach fills this gap by making use of nurse-focused approach to DES modelling.

Design Engineers and Ergonomists could use this modelling approach to design products that assist the nurses to perform their daily activity while attending to their well-being. This modelling capability can be used to provide quantifiable measures about the impact of improved usability of these devices, through decreased time requirements and their effect on 'missed care', 'care task waiting time' and biomechanical loads. Solving issue # 5 is an example of how this thesis can assist design engineers and ergonomists.

These users would either need training on how to use this DES model or could hire an industrial engineer (IE). The cost of hiring one IE could be offset by reductions in absenteeism due to illness or turnover due to unhealthy working conditions. If these technical designs and operational polices are tested before implementation, they may reduce these costs. Further research that includes an economical analysis would be required to confirm this proposition.

CHAPTER 8

CONCLUSION

An adaptable approach to creating valid nurse-focused 'flow' simulation model has been created that can quantify nurse workload, biomechanical load and quality of care under different technical design and policies. This doctoral research provides quantifiable evidence that current healthcare system polices, and design do not support nurses and quality of care delivery. Nurses are overworked that impact the quality of care. This research is the culmination of a four-year study involving a hospital collaboration. The following are conclusions arising from these demonstrator studies:

Initial Development of the Model and Demonstrator Case (RQ1)

Chapter 2 (RQ1) demonstrated the capability of developing a novel nurse-focused simulation approach that simulated the nurse's process of care delivery to quantify the impact of changing nurse-patient ratio in terms of nurse workload and quality of care. The demonstrator model shows, as nurse-patient ratio increased, nursing workload increased *(120% task in queue; 110% cumulative walking distance),* and quality of care deteriorated *(120% missed care; 20% task in queue time)*. This provided evidence that computerized modelling approaches can be used to improve quality and inform technical design and operational policy decisions.

Patient Acuity and Nurse-patient ratio (RQ2)

Chapter 3 (RQ3) further extended the model by adding new indicators for nurse workload and quality of care, while successfully quantified the effects of changing patient acuity levels and nurse-patient ratio in terms of quality of care and nurse workload indicators. The developed model shows as patient acuity levels and nurse-patient ratio increased, nurse workload increased and care quality deteriorated. In comparison to the baseline-case: *cumulative walking distance* *increased up to 18%; task in queue up to 354%* and *missed care increased up to 253%; missed care delivery time up to 354%; care delivery time up to 40%*. The modelling approach developed may offer a proactive, cost effective and safe alternative to the current trial and error methodologies.

Model Validation (RQ3)

Chapter 4 (RQ3) developing an adaptable approach to creating valid simulation models was successfully developed. ICC coefficients show an excellent agreement of *0.99, 0.99, 0.87, 0.85 between simulation and real-world outcomes*, along with a good agreement of 0.*78 for Spearman ranked correlation*. Specific modeling results include *a 'distance walked' of 7.6 to 11.1 km with a 'direct care time' of 10.4 hours with a total of 84 trips for an average of 12 'tasks in queue'*. Quality of care was represented by a *'care task waiting time' of 0.9 hours that lead to 25 'missed care' tasks, where, 36% were 'non-patient care'; 'missed care delivery time' was 2.3 hours.* By creating this adaptable modeling approach to creating valid nurse focused simulation model, it may void the need for extensive field validation study. However, this model must be used with caution.

This approach to creating valid computerized model can be used as decision support system to proactively test and quantify the impact of newer design policies and their significant trade-offs, in terms of nurse workload and quality of care. Validated simulation models have more credibility and are more favorable to the knowledge user and stakeholders. These can be used as engines to support/advocate for change in working conditions.

Geographical patient-bed assignment (RQ4)

Chapter 5 (RQ4) operationalized geographical patient-bed assignment as the average Inter-Bed distance (IBD) and average Bed-Nurse Station distance (BND). As the nurses were assigned to patient beds away from the center of the unit or spread further apart, nurse workload increased, and the quality of care is deteriorated. Under these conditions, the model revealed an increase in *distance walked by simulant-nurse by 21%* and *tasks in queue by 10%*. For quality of care, *the direct care time decreased by 8%; missed care increased by 27%; and care task waiting time by 7%.* Chapter 5 provided evidence that IBD and BND are both integral to when quantifying the impact of geographical patient-bed assignment. The chapter also reports on the creation of regression equations that address the impact of both IBD and BND in terms of indicators of quality of care and nurse workload. By extending this modeling capabilities, nurse-patient bed assignments can be better managed while addressing the trade-offs between nurse workload and quality of care.

Biomechanical load (RQ5)

Chapter 5 combines Digital Human Modelling (DHM) and DES to produce a *time-trace*, *peak* and *cumulative biomechanical load.* The *highest percentage division of cumulative biomechanical load* was for *'activity'* task group. this task group contains all patient lifting tasks such as: 'lift patient from bed and sit in chair', 'lift patient from chair', 'turn patient' etc. *Peak L4/L5 compression load and moment were 3574N and 111.58Nm respectively.* The L4/L5 compression load exceeds the NIOSH action limit of 3433N. this further provides evidence as to why nurses experience MSD and injuries. In addition, addressing RQ5 calls for an improvement of the posture for patient lifting tasks.

The effect of Geographical-patient bed assignment, Patient acuity, and Nurse-patient ratio on Biomechanical load (RQ6)

Chapter 5 further tests the developed modeling approach by testing technical design and operational policies such as geographical-patient bed assignment, patient acuity, and nurse-patient ratio. Specific modelling outcomes are reported below:

Greater distance walked for nurses lead to reduced biomechanical load and less care is delivered. As the biomechanical load for walking is much less than biomechanical load of care tasks. When nurses are assigned to patient-beds further away from the center of the unit, *the L4/L5 compression decreased by 8%; task in queue increased by 7%; distance walked increased by 16%;* and *direct care time decreased by 7%.* The quality of care also deteriorated as *missed care increased by 20%* and *care task waiting time increased by 5%.*

When nurses are assigned to more acute patients, a decrease in L4/L5 moment is observed (4%) as the task duration and frequency of most care task increase. Nurses must now spend more time delivering care given the increased care demands. Since the care demands are much higher than the current capability of nurses, quality of care is deteriorated (increased missed care). As patient acuity levels increased, *the L4/L5 moment decreased by 4%; task in queue increased by 11%; distance walked increased by 13%;* and *direct care time increased by 3%.* While the quality of care deteriorated, *specifically, missed care increased by 19%; care task waiting time increased by 1%.*

When nurses are assigned to more patients, a 'ceiling' effect on biomechanical load can be observed as the nurses does not have the time capacity to attend to this extra demand for care. *The L4/L5 moment and load* resulted in an increase of only *<0.9%; task in queue increased by 35%;*

distance walked increased by 9%; and *direct care time decreased by 55%.* The quality of care deteriorated as *missed care increased by 29%; care task waiting time increased by 9%.*

The human-factors enabled DES-modelling capability developed in this doctoral research tested several technical design and operational policies, such as, varying the nurse-to-patient ratio, acuity, geographical patient bed assignment as well as capture the biomechanical load of various nursing care activities and produced valid outcomes. This modelling approach has the potential to provide quantifiable information for difficult to quantify parameters. This multidisciplinary research provides a tool for healthcare administrators to better manage the workload of nurses by providing a proactive analysis tool that can quantify the potential impact of proposed changes in technical and design decisions. This research maybe applied by hospital managers, healthcare practitioners, researchers, architects, design engineers, ergonomists and policymakers, and provide a more cost-effective and safer alternative to the current trial and error methodologies. The model is now ready to be tested in different healthcare settings to quantify impacts of policy change in terms of nurse workload and quality of care. The DES model can provide proactive insight that may assist decision makers in creating technical design and operational policies that better manage the work demands of nurses and its subsequent impact on quality of care.

REFERENCES

Acar, I., & Butt, S. E. (2016). Modeling nurse-patient assignments considering patient acuity and travel distance metrics. *Journal of Biomedical Informatics*, *64*, 192–206. https://doi.org/10.1016/j.jbi.2016.10.006

Aiken, L. H., Clarke, S. P., Sloane, D. M., Sochalski, J., & Silber, J. H. (2001). Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. *Jama*, *288*(16), 1987–1993. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12387650

Aiken, L. S. (1991). Multiple regression: Testing and interpreting interactions. Newbury Park: Sage.

Aiken, Linda H., Clarke, S. P., Sloane, D. M., Sochalski, J. A., Busse, R., Clarke, H., … Shamian, J. (2001). Nurses' reports on hospital care in five countries. *Health Affairs*, *20*(3), 43–53. https://doi.org/10.1377/hlthaff.20.3.43

Aiken, Linda H., Sloane, D. M., Ball, J., Bruyneel, L., Rafferty, A. M., & Griffiths, P. (2018). Patient satisfaction with hospital care and nurses in England: An observational study. *BMJ Open*, *8*(1), 1–8. https://doi.org/10.1136/bmjopen-2017-019189

Aiken, Linda H, Clarke, S. P., Sloane, D. M., Lake, E. T., & Cheney, T. (2008). Effects of Hospital Care Environment on Patient Mortality and Nurse Outcomes. *Journal of Nursing Administration*, *38*(5), 223–229. https://doi.org/10.1097/01.NNA.0000312773.42352.d7.Effects

Aiken, Linda H, Clarke, S. P., Sloane, D. M., Sochalski, J., & Silber, J. H. (2002). Hospital Nurse Staffing and Patient Mortality, Emotional Exhaustion, and Job Dissatisfaction. *American Medical Association*, *288*(16), 252–254. https://doi.org/10.1097/00002800-200509000-00008

Aiken, Linda H, Sermeus, W., den Heede, K., Sloane, D. M., Busse, R., McKee, M., … Kutney-Lee,

A. (2012). Patient safety, satisfaction, and quality of hospital care: cross sectional surveys of nurses and patients in 12 countries in Europe and the United States. *BMJ*, *344*. https://doi.org/10.1136/bmj.e1717

Alexopoulos, E. C., Burdorf, A., & Kalokerinou, A. (2006). A comparative analysis on musculoskeletal disorders between Greek and Dutch nursing personnel. *International Archives of Occupational and Environmental Health*, *79*(1), 82–88. https://doi.org/10.1007/s00420-005-0033-z

Alghamdi, M. G. (2016). Nursing workload: A concept analysis. *Journal of Nursing Management*, *24*(4), 449–457. https://doi.org/10.1111/jonm.12354

American Association of Colleges of Nursing. (2019). *Fact sheet: Nursing Shortage*.

Arsenault Knudsen, É. N., Brzozowski, S. L., & Steege, L. M. (2018). Measuring Work Demands in Hospital Nursing: A Feasibility Study. *IISE Transactions on Occupational Ergonomics and Human Factors*, *6*(3–4), 143–156. https://doi.org/10.1080/24725838.2018.1509910

Ausserhofer, D., Zander, B., Busse, R., Schubert, M., De Geest, S., Rafferty, A. M., … Achterberg, T. van. (2014). Prevalence, patterns and predictors of nursing care left undone in European hospitals: results from the multicountry cross-sectional RN4CAST study. *BMJ Quality & Safety*, *23*(2), 126–135. https://doi.org/10.1136/bmjqs-2013-002318

Ausserhofer, D., Zander, B., Busse, R., Schubert, M., Geest, S. De, Rafferty, A. M., … Sjetne, I. S. (2014). Prevalence , patterns and predictors of nursing care left undone in European hospitals : results from the multicountry cross-sectional RN4CAST study. https://doi.org/10.1136/bmjqs-2013-002318

Australia Nursing Federation. (2009). *Ensuring quality , safety and positive patient outcomes*.

Banks, J., Carson, J. S. I., Nelson, N. L., & Nicol, D. M. (2005). *Discrete-Event System Simulation* (4th ed.). Prentice Hall International Series in Industrial and Systems Engineering.

Baril, C., Gascon, V., Miller, J., & Bounhol, C. (2016). Studying nurse workload and patient waiting time in a hematology-oncology clinic with discrete event simulation. *IIE Transactions on Healthcare Systems Engineering*, *6*(4), 223–234. https://doi.org/10.1080/19488300.2016.1226212

Barker, L. M., & Nussbaum, M. A. (2011). Fatigue, performance and the work environment: A survey of registered nurses. *Journal of Advanced Nursing*, *67*(6), 1370–1382. https://doi.org/10.1111/j.1365-2648.2010.05597.x

Barnes, S. L., Morgan, D. J., Pineles, L., & Harris, A. D. (2018). Significance of multi-site calibration for agent-based transmission models. *IISE Transactions on Healthcare Systems Engineering*, *8*(2), 131–143. https://doi.org/10.1080/24725579.2018.1431739

Bartko, J. J. (1966). The Intraclass Correlation Coefficient as a Measure of Relability. *Psychological Reports*, *19*, 3–11.

Ben-Assuli, O., Sagi, D., Leshno, M., Ironi, A., & Ziv, A. (2015). Improving diagnostic accuracy using EHR in emergency departments: A simulation-based study. *Journal of Biomedical Informatics*, *55*, 31–40. https://doi.org/10.1016/j.jbi.2015.03.004

Benda, N. C., Blumenthal, H. J., Hettinger, A. Z., Hoffman, D. J., LaVergne, D. T., Franklin, E. S., … Bisantz, A. M. (2018). Human Factors Design in the Clinical Environment: Development and Assessment of an Interface for Visualizing Emergency Medicine Clinician Workload. *IISE Transactions on Occupational Ergonomics and Human Factors*, *6*(3–4), 225–237. https://doi.org/10.1080/24725838.2018.1522392

Bernard, B. P. (Ed.). (1997). *Musculoskeletal Disorders and Workplace Factors: A Critical Review of Epidemiologic Evidence for Work-Related Musculoskeletal Disorders of the Neck, Upper Extremity, and Low Back*. Cincinnati, OH: U.S. Department of Health and Human Services, National Institute for Occupational Safety and Health. Retrieved from https://www.cdc.gov/niosh/docs/97-141/pdfs/97-141.pdf

Blecic, D. D. (1999). Measurements of journal use: an analysis of the correlations between three methods. *Bulletin of the Medical Library Association*, *87*(1), 20–25. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/9934525%0Ahttp://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC226509

Borg, G. (1990). Psychophysical scaling with applications in physical work and the perception of exertion. *Scandinavian Journal of Work, Environment and Health*, *16*(SUPPL. 1), 55–58. https://doi.org/10.5271/sjweh.1815

Borg, G. (1998). Borg´s perceived exertion and pain scales. *Human Kinetics*, (July 1998), 104 vii. https://doi.org/10.1097/00005768-199809000-00018

Boucherie, R. J., Hans, E. W., & Hartmann, T. (2012). Health care logistics and space: Accounting for the physical build environment. *Proceedings - Winter Simulation Conference*, (January). https://doi.org/10.1109/WSC.2012.6465222

Brazil, V., Purdy, E. I., & Bajaj, K. (2019). Connecting simulation and quality improvement: how can healthcare simulation really improve patient care? *BMJ Quality & Safety*, bmjqs-2019-009767. https://doi.org/10.1136/bmjqs-2019-009767

Brennan, C. W. (2011). Patient acuity: Concept clarification and psychometric assessment. *ProQuest Dissertations and Theses*, 137.

Brennan, C. W., Daly, B. J., & Jones, K. R. (2013). State of the science: the relationship between nurse staffing and patient outcomes. *Western Journal of Nursing Research*, *35*(6), 760–794. https://doi.org/10.1177/0193945913476577

Bridger, R. S. (Ed.). (2009). *Introduction to Ergonomics* (Third Edit). CRC Press Taylor & Francis Group.

Bureau of Labor Statistics. (2011a). *Nonfatal Occupational Injuries and Illnesses Requiring Days Away from Work. US Department of Labor, USDL, 2010*.

Bureau of Labor Statistics. (2011b). *U.S. Department of Labor, Occupational Outlook Handbook: A review of 50 years of change. Monthly Labor Review*.

Butt, S., Fredericks, T., Kumar, A., Wahl, J., Harrelson, K., Means, S., … Brown, E. (2004). An evaluation of physiological work demands on registered nurses over a 12-hour shift. In *Proceedings of the XVIII Annual International Occupational Ergonomics and Safety Conference (ISOES), Houston, TX, USA*.

Cabrera, E., Taboada, M., Iglesias, M. L., Epelde, F., & Luque, E. (2012). Simulation optimization for healthcare emergency departments. *Procedia Computer Science*, *9*, 1464–1473. https://doi.org/10.1016/j.procs.2012.04.161

Campbell, S. M., Roland, M. O., & Buetow, S. A. (2000). Defining quality of care. *Social Science & Medicine*, *51*, 1611–1625.

Canadian Federation of Nurses Unions. (2015). *Overtime and Absenteeism Factsheet*.

Canadian Federation of Nurses Unions. (2017a). Enough is Enough: Putting a Stop to Violence in the Health Care Sector.

Canadian Federation of Nurses Unions. (2017b). *Quick Facts 2017: Trends in Own Illness-or Disability-Related Absenteeism and Overtime among Publicly-Employed Registered Nurses*. Retrieved from https://nursesunions.ca/wp-content/uploads/2017/05/Quick_Facts_Absenteeism-and-Overtime-2017-Final.pdf

Canadian Federation of Nurses Unions. (2017c). Quick Facts 2017, 1–6.

Canadian Institute of Health Information. (2017). *Regulated Nurses, 2016*.

Canadian Nurses Association. (2015). How many RNs do we need? How many do we have?, 4. Retrieved from https://www.cna-aiic.ca/-/media/cna/page-content/pdf-en/rn_highlights_e.pdf?la=en&hash=22B42E6B470963D8EDEAC3DCCBD026EDA1F6468D

Canadian Nursing Advisory Committee- Advisory Committee on Health Human Resources. (2002). Our health, our future: creating quality workplaces for Canadian nurses, (July), 1–91. Retrieved from http://rcrpp.org/documents/30762_en.pdf

Carayon, P. (2010). Human factors in patient safety as an innovation. *Applied Ergonomics*, *41*(5), 657–665. https://doi.org/10.1016/j.apergo.2009.12.011

Carayon, P., Cartmill, R., Blosky, M. A., Brown, R., Hackenberg, M., Hoonakker, P., … Walker, J. M. (2011). ICU nurses' acceptance of electronic health records. *Journal of the American Medical Informatics Association*, *18*(6), 812–819. https://doi.org/10.1136/amiajnl-2010-000018

Carayon, P., Schoofs Hundt, A., Karsh, B.-T., Gurses, A. P., Alvarado, C. J., Smith, M., & Flatley Brennan, P. (2006). Work system design for patient safety: the SEIPS model. *Quality & Safety in Health Care*, *15 Suppl 1*, i50-8. https://doi.org/10.1136/qshc.2005.015842

Carayon, P., Wetterneck, T. B., Rivera-Rodriguez, A. J., Hundt, A. S., Hoonakker, P., Holden, R., & Gurses, A. P. (2014). Human factors systems approach to healthcare quality and patient safety. *Applied Ergonomics*, *45*(1), 14–25. https://doi.org/10.1016/j.apergo.2013.04.023

Carayon, P., Xie, A., & Kianfar, S. (2014). Human factors and ergonomics as a Patient safety practice. *BMJ Quality and Safety*, *23*(3), 196–205. https://doi.org/10.1136/bmjqs-2013-001812

Caruso, C. C. (2014). Negative impacts of shiftwork and long work hours. *Rehabilitation Nursing*, *39*(1), 16-25. https://doi.org/doi:10.1002/rnj.107

Casier, G., Casier, K., Ooteghem, J. Van, & Verbrugge, S. (2012). Application of a Discrete Event Simulator for Healthcare Processes.

Casner, S., & Gore, B. (2010). Measuring and evaluating workload: A primer. *NASA Technical Memorandum*, (2010–216395).

Cavagna, G. A., & Margaria, R. (1966). Mechanics of walking. *Journal of Applied Physiology*, *21*(1), 271–278. https://doi.org/10.1152/jappl.1966.21.1.271

Chaffin, D. B. (2007). Human Motion Simulation for Vehicle and Workplace Design. *Human Factors and Ergonomics in Manufacturing*, *20*(5), 475–484. https://doi.org/10.1002/hfm

Chapanis, A., & Safrin, M. A. (1960). Of misses and medicines. *Journal of Chronic Diseases*, *12*(4), 403–408. https://doi.org/10.1016/0021-9681(60)90065-5

Chapman, R., Rahman, A., Courtney, M., & Chalmers, C. (2016). Impact of teamwork on missed care in four Australian hospitals. *Journal of Clinical Nursing*, *26*, 170–181. https://doi.org/10.1111/jocn.13433

Choudhary, R., Bafna, S., Heo, Y., Hendrich, A., & Chow, M. (2010). A predictive model for computing the influence of space layouts on nurses’ movement in hospital units. *Journal of Building Performance Simulation*, *3*(3), 171–184. https://doi.org/10.1080/19401490903174280

Chuang, C. H., Tseng, P. C., Lin, C. Y., Lin, K. H., & Chen, Y. Y. (2016). Burnout in the intensive care unit professionals: A systematic review. *Medicine (United States)*, *95*(50), e5629. https://doi.org/10.1097/MD.0000000000005629

Cignarale, C. (2013). Analysis and optimization of patient bed assignments within a hospital unit while considering isolation requirements.

Corchia, C., Fanelli, S., Gagliardi, L., Bellù, R., Zangrandi, A., Persico, A., & Zanini, R. (2016). Work environment, volume of activity and staffing in neonatal intensive care units in Italy:

Results of the sonar-nurse study. *Italian Journal of Pediatrics*, *42*(1), 1–8. https://doi.org/10.1186/s13052-016-0247-6

Dabney, B. W., & Kalisch, B. J. (2015). Nurse Staffing Levels and Patient-Reported Missed Nursing Care. *Journal of Nursing Care Quality*, *30*(4), 306–312. https://doi.org/10.1097/NCQ.0000000000000123

Daly, B. J., & Brennan, C. W. (2009). Patient acuity: A concept analysis. *Journal of Advanced Nursing*, *65*(5), 1114–1126. https://doi.org/10.1111/j.1365-2648.2008.04920.x

Davey, M. M., Cummings, G., Newburn-Cook, C. V., & Lo, E. A. (2009). Predictors of nurse absenteeism in hospitals: A systematic review. *Journal of Nursing Management*, *17*(3), 312–330. https://doi.org/10.1111/j.1365-2834.2008.00958.x

Dawson, D., & Reid, K. (1997). Fatigue, alcohol and performance impairment. *Nature*, *388*(6639), 235. https://doi.org/10.1038/40775

Djukic, M., T Kovner, C., Brewer, C., Fatehi, F., & D Cline, D. (2012). Work environment factors other than staffing associated with nurses' ratings of patient care quality. *JONA: The Journal of Nursing Administration*, *42*(Supplement), S17–S26. https://doi.org/10.1097/01.NNA.0000420391.95413.88

Dode, P. (2012). *The Integration of Human Factors into Discrete Event Simulation and Technology Acceptance in Engineering Design*. Ryerson Univeristy. Retrieved from http://digitalcommons.ryerson.ca/dissertations

Dode, P. (Pete), Greig, M., Zolfaghari, S., & Neumann, W. P. (2016). Integrating human factors into discrete event simulation: a proactive approach to simultaneously design for system performance and employees' well being. *International Journal of Production Research*, *54*(10), 3105. https://doi.org/10.1080/00207543.2016.1166287

Donabedian, A. (1978). The quality of medical care. *Science*, *200*(4344), 856–864. https://doi.org/10.1126/science.417400

Drotz, E., & Poksinska, B. (2014). Lean in healthcare from employees' perspectives. *Journal of Health Organisation & Management*, *2*(28), 177–195. https://doi.org/10.1108/JHOM-03-2013-0066

Duguay, C., & Chetouane, F. (2007). Modelling andimproving emergency department systems using discrete event simulation. *Computer Science and Software Engineering*, *1*(63), 311– 320.

Earle, C. C., & Ganz, P. A. (2012). Cancer survivorship care: don't let the perfect be the enemy of the good. *Journal of Clinical Oncology*, *30*(30), 3764–3768. https://doi.org/10.1200/JCO.2012.41.7667

Farid, M. (2017). *Modelling Workload To Quality Using System Dynamics In Manufacturing And Healthcare*. Ryerson University.

Farrington, M., Trundle, C., Redpath, C., & Anderson, L. (2000). Effects on nursing workload of different methicillin-resistant Staphylococcus aureus (MRSA) control strategies. *Journal of Hospital Infection*, *46*(2), 118–122. https://doi.org/10.1053/jhin.2000.0808

Fatemi, M., Millan, J., Stevenson, J., Yu, T., & O'Young, S. (2008). Discrete event control of an unmanned aircraft. *2008 9th International Workshop on Discrete Event Systems*, (July 2015). https://doi.org/10.1109/WODES.2008.4605971

Feehan, L. M., Geldman, J., Sayre, E. C., Park, C., Ezzat, A. M., Yoo, J. Y., … Li, L. C. (2018). Accuracy of fitbit devices: Systematic review and narrative syntheses of quantitative data. *Journal of Medical Internet Research*, *20*(8). https://doi.org/10.2196/10527

Fischer, S. L., Albert, W. J., McClellan, A. J., & Callaghan, J. P. (2007). Methodological considerations for the calculation of cumulative compression exposure of the lumbar spine: A sensitivity analysis on joint model and time standardization approaches. *Ergonomics*, *50*(9), 1365–1376. https://doi.org/10.1080/00140130701344042

Gaba, D. M. (1999). Anaesthesiology as a model for patient safety in health care, 785–788.

Gaba, D. M. (2007). The future vision of simulation in healthcare. *Simulation in Healthcare : Journal of the Society for Simulation in Healthcare*, *2*(2), 126–135. https://doi.org/10.1097/01.SIH.0000258411.38212.32

Galletta, M., Portoghese, I., Ciuffi, M., Sancassiani, F., Aloja, E. D', & Campagna, M. (2016). Working and Environmental Factors on Job Burnout: A Cross-sectional Study Among Nurses. *Clinical Practice & Epidemiology in Mental Health*, *12*(1), 132–141. https://doi.org/10.2174/1745017901612010132

Garrett, C. (2008). The Effect of Nurse Staffing Patterns on Medical Errors and Nurse Burnout. *AORN Journal*, *87*(6). https://doi.org/10.1016/j.aorn.2008.01.022

Gingras, J., de Jonge, L. A., & Purdy, N. (2010). Prevalence of dietitian burnout. *Journal of Human Nutrition and Dietetics*, *23*(3), 238–243. https://doi.org/10.1111/j.1365-277X.2010.01062.x

Goodman, C. W. (2017). Nurse-managed transitional beds as a method of increasing geographic placement of an academic inpatient service. *BMJ Open Quality*, *6*(2), e000078. https://doi.org/10.1136/bmjoq-2017-000078

Gormanns, N., Lasota, M., McCracken, M., & Zitikyte, D. (2011). *Quick Facts: Absenteeism and Overtime. Adapted from: Trends in Own Illness or Disability-Related Absenteeism and Overtime among Publicly-Employed Registered Nurses – Summary of Key Findings. Report prepared by Informetrica Limited for Canadian Federation* .

Greig, Michael A, Village, J., Salustri, F. A., Zolfaghari, S., & Neumann, W. P. (2018). A tool to predict physical workload and task times from workstation layout design data. *International Journal of Production Research*, *56*(16), 5306–5323. https://doi.org/10.1080/00207543.2017.1378827

Greig, Michael Alexander. (2016). *Developing Human Factors Metrics and Tools to Support Management and Design of Production (doctoral thesis)*.

Griffiths, P., Dall'Ora, C., Simon, M., Ball, J., Lindqvist, R., Rafferty, A.-M., … Aiken, L. H. (2014). Nurses' Shift Length and Overtime Working in 12 European Countries. *Medical Care*, *52*(11), 975–981. https://doi.org/10.1097/mlr.0000000000000233

Griffiths, P., Maruotti, A., Recio Saucedo, A., Redfern, O. C., Ball, J. E., Briggs, J., … Smith, G. B. (2018). Nurse staffing, nursing assistants and hospital mortality: Retrospective longitudinal cohort study. *BMJ Quality and Safety*, 1–9. https://doi.org/10.1136/bmjqs-2018-008043

Guido, R., Groccia, M. C., & Conforti, D. (2018). An efficient matheuristic for offline patient-to-bed assignment problems. *European Journal of Operational Research*, *268*(2), 486–503. https://doi.org/10.1016/j.ejor.2018.02.007

Gunal, M. M., & Pidd, M. (2010). Discrete event simulation for performance modelling in health care: a review of the literature. *Journal of Simulation*, *4*(1), 42–51.

https://doi.org/10.1057/jos.2009.25

Günal, M. M., & Pidd, M. (2010). Discrete event simulation for performance modelling in health care: A review of the literature. *Journal of Simulation*, *4*(1), 42–51. https://doi.org/10.1057/jos.2009.25

Hanson, L., Högberg, D., Lundström, D., & Wårell, M. (2009). Application of Human Modelling in Health Care Industry. In V. G. Duffy (Ed.), *Digital Human Modeling* (pp. 521–530). Berlin, Heidelberg: Springer Berlin Heidelberg.

Heinen, M. M., van Achterberg, T., Schwendimann, R., Zander, B., Matthews, A., Kózka, M., … Schoonhoven, L. (2013). Nurses' intention to leave their profession: A cross sectional observational study in 10 European countries. *International Journal of Nursing Studies*, *50*(2). https://doi.org/10.1016/j.ijnurstu.2012.09.019

Hendrich, A., Chow, M. P., Skierczynski, B. A., & Lu, Z. (2008). A 36-hospital time and motion study: how do medical-surgical nurses spend their time? *The Permanente Journal*, *12*(3), 25–34. Retrieved from http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3037121&tool=pmcentrez&rendertype=abstract

Hendry, C., & Walker, A. (2004). Priority setting in clinical nursing practice: Literature review. *Journal of Advanced Nursing*, *47*(4), 427–436. https://doi.org/10.1111/j.1365-2648.2004.03120.x

Hignett, S., & McAtamney, L. (2000). Rapid Entire Body Assessment (REBA). *Applied Ergonomics*, *31*(2), 201–205. https://doi.org/10.1016/S0003-6870(99)00039-3

Hoad, K., Robinson, S., & Davies, R. (2008). Automating warm-up length estimation. *Proceedings - Winter Simulation Conference*, 532–540. https://doi.org/10.1109/WSC.2008.4736110

Holden, R. J., Carayon, P., Gurses, A. P., Hoonakker, P., Hundt, A. S., Ozok, A. A., & Rivera-Rodriguez, A. J. (2013). SEIPS 2.0: A human factors framework for studying and improving the work of healthcare professionals and patients. *Ergonomics*, *56*(11), 1–30. https://doi.org/10.1080/00140139.2013.838643

Holmes, M. W. R., Hodder, J. N., & Keir, P. J. (2010). Continuous assessment of low back loads in long-term care nurses. *Ergonomics*, *53*(9), 1108–1116. https://doi.org/10.1080/00140139.2010.502253

Hua, Y., Becker, F., Wurmser, T., Bliss-Holtz, J., & Hedges, C. (2012). Effects of nursing unit spatial layout on nursing team communication patterns, quality of care, and patient safety. *Health Environments Research and Design Journal*, *6*(1), 8–38. https://doi.org/10.1177/193758671200600102

Hughes, R. G. (2008). *Patient safety and quality: an evidence-based handbook for nurses. Agency for Healthcare Research and Quality, US Department of Health and Human Services*. https://doi.org/AHRQ Publication No. 08-0043

Hurst, K. (2018). Relationships between patient dependency, nursing workload and quality. *International Journal of Nursing Studies*, *42*(1), 75–84. https://doi.org/10.1016/j.ijnurstu.2004.05.011

Infor. (2016). Infor Named Market Leader in Hospital Operations Management IT. Retrieved from https://www.infor.com/news/infor-named-market-leader-in-hospital-operations-management-it

International Council of Nurses. (2015). *International Classification for Nursing Practice (ICNP®)*.

International Ergonomics Association. (2018). Definition and Domains of Ergonomics. Retrieved from http://www.iea.cc/whats/index.html

Iwata, C., & Mavris, D. (2013). Object-oriented discrete event simulation modeling environment for aerospace vehicle maintenance and logistics process. *Procedia Computer Science*, *16*, 187–196. https://doi.org/10.1016/j.procs.2013.01.020

Jang, R., Karwowski, W., Quesada, P. M., Rodrick, D., Sherehiy, B., Cronin, S. N., & Layer, J. K. (2007). Biomechanical evaluation of nursing tasks in a hospital setting. *Ergonomics*, *50*(11), 1835–1855. https://doi.org/10.1080/00140130701674661

Jiang, H., Karwowski, W., & Ahram, T. (2012). Application of System Dynamics Modeling for the Assessment of Training Performance Effectiveness. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *56*(1), 1030–1033. https://doi.org/10.1177/1071181312561215

Judy Lynn Village. (2014). *THE INTEGRATION OF HUMAN FACTORS INTO A COMPANY`S PRODUCTION DESIGN PROCESS*.

Jun, J. B., Jacobson, S. H., & Swisher, J. R. (1999). Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society*, *50*(2), 109–123. https://doi.org/10.1057/palgrave.jors.2600669

Kalisch, B. J., & Williams, R. A. (2009). Development and psychometric testing of a tool to measure missed nursing care. *Journal of Nursing Administration*, *39*(5), 211–219. https://doi.org/http://dx.doi.org/10.1097/NNA.0b013e3181a23cf5

Kanji, S., Buffie, J., Hutton, B., Bunting, P. S., Singh, A., McDonald, K., … Hebert, P. C. (2005). Reliability of point-of-care testing for glucose measurement in critically ill adults. *Critical Care Medicine*, *33*(12), 2778–2785. https://doi.org/10.1097/01.CCM.0000189939.10881.60

Karasek, R. A. (1979). Job Demands, Job Decision Latitude, and Mental Strain: Implications for Job Redesign. *Administrative Science Quarterly*, *24*(2), 285–308.

Kazmierczak, K., Neumann, W. P., & Winkel, J. (2007). A Case Study of Serial-Flow Car Disassembly: Ergonomics, Productivity and Potential System Performance. *Human Factors and Ergonomics in Manufacturing*, *17*(4), 331–351. https://doi.org/10.1002/hfm

Kiani, A. (2016). Investigation of Agent-Based Modelling for Inpatient Healthcare systems.

Kieft, R. A. M. M., De Brouwer, B. B. J. M., Francke, A. L., & Delnoij, D. M. J. (2014). How nurses and their work environment affect patient experiences of the quality of care: A qualitative study. *BMC Health Services Research*, *14*(1), 1–10. https://doi.org/10.1186/1472-6963-14-249

Kilkenny, M. F., & Robinson, K. M. (2018). Data quality: "Garbage in – garbage out." *Health Information Management Journal*, *47*(3), 103–105. https://doi.org/10.1177/1833358318774357

Kohn, L. T., Corrigan, J. M., & Molla, S. (1999). To Err Is Human. *Medicine*, *126*(November), 312. https://doi.org/10.1017/S095026880100509X

Komashie, A., & Mousavi, A. (2005). Modeling Emergency Departments Using Discrete Event Simulation Techniques. In *Proceedings of the 37th Conference on Winter Simulation* (pp. 2681–2685). Winter Simulation Conference. Retrieved from http://dl.acm.org/citation.cfm?id=1162708.1163203

Kramer, M., & Schmalenberg, C. (2008). The practice of clinical autonomy in hospitals: 20 000 nurses tell their story. *Critical Care Nurse*, *28*(6), 58–71. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/19047696

Kucera, K. L., Schoenfisch, A. L., McIlvaine, J., Becherer, L., James, T., Yeung, Y. L., … Lipscomb, H. J. (2019). Factors associated with lift equipment use during patient lifts and transfers by hospital nurses and nursing care assistants: A prospective observational cohort study. *International Journal of Nursing Studies*, *91*, 35–46. https://doi.org/10.1016/j.ijnurstu.2018.11.006

Lamé, G., & Dixon-Woods, M. (2018). Using clinical simulation to study how to improve quality and safety in healthcare. *BMJ Simulation and Technology Enhanced Learning*, bmjstel-2018-000370. https://doi.org/10.1136/bmjstel-2018-000370

Laslett, B., & Rapoport, R. (1975). Collaborative Interviewing and Interactive Research. *Journal of Marriage and Family*, *37*(4), 968–977. https://doi.org/10.4135/9781452286143.n382

Lebcir, R., Demir, E., Ahmad, R., Vasilakis, C., & Southern, D. (2017). A discrete event simulation model to evaluate the use of community services in the treatment of patients with Parkinson's disease in the United Kingdom. *BMC Health Services Research*, *17*(1), 1–14. https://doi.org/10.1186/s12913-017-1994-9

Letiche, H. (2008). Making healthcare care: Managing via simple guiding principles. *IAP*.

Letvak, S., Ruhm, C., & Gupta, S. (2012). Nurses presenteeism and its effects on self-reported quality of care and costs. *American Journal of Nursing*, *112*(2), 30–38.

Liang, B., & Turkcan, A. (2016). Acuity-based nurse assignment and patient scheduling in oncology clinics. *Health Care Management Science*, *19*(3), 207–226. https://doi.org/10.1007/s10729-014-9313-z

Luoma, H. (2006). Planning and Designing Highly Functional Nurses' Stations. *Healthcare Design*. Retrieved from https://www.healthcaredesignmagazine.com/architecture/planning-and-designing-highly-functional-nurses-stations/

Malhotra, S., Jordan, D., Shortliffe, E., & Patel, V. L. (2007). Workflow modeling in critical care: Piecing together your own puzzle. *Journal of Biomedical Informatics*, *40*(2), 81–92.

https://doi.org/10.1016/j.jbi.2006.06.002

Maslach, C., & Jackson, S. E. (1981). The measurement of experienced burnout. *Journal of Organizational Behavior*, *2*(2), 99–113. https://doi.org/10.1002/job.4030020205

McAtamney, L., & Corlett, E. N. (1993). RULA: a survey method for the investigation of world-related upper limb disorders. *Applied Ergonomics*, *24*(2), 91–99. https://doi.org/10.1016/0003-6870(93)90080-S

McDonald, J. H. (2014). *Handbook of Biological Statistics* (3rd ed.). Baltimore, Maryland: Sparky House Publishing.

McGillis Hall, L., Doran, D., Tregunno, D., McCutcheon, A., O'Brien-Pallas, L., Tranmer, J., … Thomson, D. (2005). *Quality Work Environments for Nurse and Patient Safety*. (L. McGillis Hall, Ed.). Jones and Barlett Publishers, Inc.

Meischke, H., THo, M. T., Eisenberg, Mickey, S., Schaeffer, S. M., & Larsen, M. P. (1995). Reasons Patients With Chest Pain Delay or Do Not Call 911. *Annals of Emergency Medicine*, *25*(2), 193–197.

Mekitiak, M., Greig, M., & Neumann, W. P. (2016). Fitting Ergonomics to the Engineers. *Centre of Research Expertise for the Prevention of Musculoskeletal Disorders (CRE-MSD) Position Paper*, (4164–3). Retrieved from https://uwaterloo.ca/centre-of-research-expertise-for-the-prevention-of-musculoskeletal-disorders/sites/ca.centre-of-research-expertise-for-the-prevention-of-musculoskeletal-disorders/files/uploads/files/4164-3_position_paper_2016_-_mekitiak_greig_neumann

Mohammadi, M., & Shamohammadi, M. (2012). Queuing Analytic Theory Using WITNESS Simulation in Hospital Pharmacy. *Ijens.Org*, (06), 20–27. Retrieved from http://www.ijens.org/Vol_12_I_06/123806-9494-IJET-IJENS.pdf

Moraros, J., Lemstra, M., & Nwankwo, C. (2016). Lean interventions in healthcare: Do they actually work? A systematic literature review. *International Journal for Quality in Health Care*, *28*(2), 150–165. https://doi.org/10.1093/intqhc/mzv123

Morelli, A. (2007). Implications of Nursing Station Design on Nurses ' Psychosocial Health and Work Behavior.

Mullinax, C., & Lawley, M. (2002). Assigning patients to nurses in neonatal intensive care. *Journal of the Operational Research Society*, *53*(1), 25–35. https://doi.org/10.1057/palgrave/jors/2601265

Myny, D., Van Goubergen, D., Limère, V., Gobert, M., Verhaeghe, S., & Defloor, T. (2010). Determination of standard times of nursing activities based on a nursing minimum dataset. *Journal of Advanced Nursing*, *66*(1), 92–102. https://doi.org/10.1111/j.1365-2648.2009.05152.x

National Advisory Group on the Safety of Patients in England. (2013). A promise to learn – a commitment to act. *Department of Health*, (August), 46. https://doi.org/10.1136/bmjqs-2014-003702

National Institute for Health and Care Excellence. (2014). Safe staffing for nursing in adult inpatient wards in acute hospitals : NICE safe staffing guideline, (May), 83.

Nelson, G. S., Wickes, H., & English, J. T. (1994). Manual Lifting: The NIOSH Work Practices Guide for Manual Lifting Determining Acceptable Weights of Lift. Retrieved from http://www.hazardcontrol.com/print.php?fs=ml-mh&p=NIOSH-guidelines-and-revised-formula

Neumann, W. P., & Medbo, P. (2009). Integrating human factors into discrete event simulations of parallel flow strategies. *Production Planning and Control*, *20*(1), 3–16. https://doi.org/10.1080/09537280802601444

Neumann, W. P., Wells, R., & Norman, R. W. (1999). 4D WATBAK: Adapting research tools and epidemiological findings to software for easy application by industrial personnel. *International Conference on Computer-Aided Ergonomics and Safety, 1999, Barcelona, Spain.* https://doi.org/10.1016/S0268-0033(98)00020-5

Neumann, W. Patrick, & Dul, J. (2010). Human factors: spanning the gap between OM and HRM. *International Journal of Operations & Production Management*, *30*(9), 923–950. https://doi.org/10.1108/01443571011075056

Neumann, W.P., Steege, L. M., Jun, G. T., & Wiklund, M. (2018). Ergonomics and Human Factors in Healthcare System Design – An Introduction to This Special Issue. *IISE Transactions on Occupational Ergonomics and Human Factors*, *6*(3–4), 109–115.

https://doi.org/10.1080/24725838.2018.1560927

Neumann, W.P., Winkel, J., Medbo, L., Magneberg, R., & Mathiassen, S. E. (2006). Production system design elements influencing productivity and ergonomics. *International Journal of Operations & Production Management*, *26*(8), 904–923. https://doi.org/10.1108/01443570610678666

Neumann, W P, Kihlberg, S., Medbo, P., Mathiassen, S. E., & Winkel, J. (2002). A case study evaluating the ergonomic and productivity impacts of partial automation strategies in the electronics industry. *International Journal of Production Research*, *40*(16), 4059–4075. https://doi.org/10.1080/00207540210148862

Neumann, Walther Patrick, Dixon, S. M., & Nordvall, A.-C. (2014). Consumer demand as a driver of improved working conditions: the 'Ergo-Brand' proposition. *Ergonomics*, *57*(8), 1113–1126. https://doi.org/10.1080/00140139.2014.917203

Norman, R., Wells, R., & Neumann, P. (1998). A comparison of peak vs cumulative physical work exposure risk factors for the reporting low back pain in the automotive industry.

Norris, B. J. (2012). Systems human factors: how far have we come? *BMJ Quality & Safety*, *21*(9), 713–714. https://doi.org/10.1136/bmjqs-2011-000476

Nursing Task Force. (1999). GoodNursing, GoodHealth : An Investment for the 21st Century. *Ministry of Health and Long-TermCare,Ontario, Canada.*

O'Brien-Pallas, L., & Baumann, A. (1992). Quality of nursing worklife issues--a unifying framework. *Canadian Journal of Nursing Administration*, *5*(2), 12–16.

Occupational Safety and Health Administration. (2013). *Worker Safety in Your Hospital*. Retrieved from https://www.osha.gov/dsg/hospitals/documents/1.1_Data_highlights_508.pdf

Oliva, R., & Sterman, J. D. (2001). Cutting Corners and Working Overtime: Quality Erosion in the Service Industry. *Management Science*, *47*(7), 894–914. https://doi.org/10.1287/mnsc.47.7.894.9807

Ontario Ministry of Labor. (2017). *The Changing Workplaces Review: An Agenda for Workplace Rights*. Retrieved from https://files.ontario.ca/books/mol_changing_workplace_report_eng_2_0.pdf

Oreskes, N., Shrader-Frechette, K., & Belitz, K. (1994). Verification , Validation , and Confirmation of Numerical Models in the Earth Sciences. *Science*, *263*(5147), 641–646. Retrieved from https://www.jstor.org/stable/2883078

Parente, C. A., Salvatore, D., Gallo, G. M., & Cipollini, F. (2018). Using overbooking to manage no-shows in an Italian healthcare center. *BMC Health Services Research*, *18*(1), 1–12. https://doi.org/10.1186/s12913-018-2979-z

Park, S. H., Weaver, L., Mejia-Johnson, L., Vukas, R., & Zimmerman, J. (2015). An Integrative Literature Review of Patient Turnover in Inpatient Hospital Settings. *Western Journal of Nursing Research*, 0193945915616811-. https://doi.org/10.1177/0193945915616811

Parker, S. (2003). Longitudinal effects of lean production on employee outcomes and the mediating role of work characteristics. *Journal of Applied Psychology*, *88*(4), 620–634.

Paul, G., & Quintero-Duran, M. (2015). Ergonomic assessment of hospital bed moving using DHM Siemens JACK. *Proceedings of the 19th Triennial Congress of the International Ergonomics Association*, (August), 1–6. Retrieved from http://eprints.qut.edu.au/86239/3/86239.pdf

Perez, J. (2011). Virtual Human Factors Tools for Proactive Ergonomics - Qualitative Exploration and Method Development. *Mechanical and Industrial Engineering*, *MASc*, 68. Retrieved from http://digitalcommons.ryerson.ca/dissertations/475/

Perez, J., de Looze, M. P., Bosch, T., & Neumann, W. P. (2014). Discrete event simulation as an ergonomic tool to predict workload exposures during systems design. *International Journal of Industrial Ergonomics*, *44*(2), 298–306. https://doi.org/10.1016/j.ergon.2013.04.007

Pope, M. H., Andersson, G. B. J., Frymoyer, J. W., & Chaffin, D. B. (Eds.). (1991). *Occupational low back pain: assessment, treatment, and prevention*. St Louis, MO: Mosby-Year Book, Inc.

Portoghese, I., Galletta, M., Coppola, R. C., Finco, G., & Campagna, M. (2014). Burnout and workload among health care workers: The moderating role of job control. *Safety and Health at Work*, *5*(3), 152–157. https://doi.org/10.1016/j.shaw.2014.05.004

Potter, P., Wolf, L., Boxerman, S., Grayson, D., Sledge, J., Dunagan, C., & Evanoff, B. (2005). Understanding the cognitive work of nursing in the acute care environment. *The Journal of Nursing Administration*, *35*(7–8), 327–335. https://doi.org/10.1097/00005110-200507000-

00004

Potter, P., Wolf, L., Boxerman, S., Grayson, D., Sledge, J., Dunagan, C., & Evanoff, B. (2009). An Analysis of Nurses ' Cognitive Work : A New Perspective for Understanding Medical Errors. *International Journal of Healthcare Information Systems and Informatics*, *4*(3), 39–52. Retrieved from http://www.igi-global.com/viewtitlesample.aspx?id=3978

Punnett, L., & Wegman, D. H. (2004). Work-related musculoskeletal disorders: The epidemiologic evidence and the debate. *Journal of Electromyography and Kinesiology*, *14*(1), 13–23. https://doi.org/10.1016/j.jelekin.2003.09.015

Purdy, N., Laschinger, H. K. S., Finegan, J., Kerr, M., & Olivera, F. (2010). Effects of work environments on nurse and patient outcomes, 901–913. https://doi.org/10.1111/j.1365-2834.2010.01172.x

Qureshi, Sadeem M., Purdy, N., & Neumann, W. P. (2016). Predicting Nursing Workload using Discrete Event Simulation. In *Proceedings of the Association of Canadian Ergonomists (ACE) Conference 2016: Harnessing the Power of Ergonomics, Niagara Falls, ON Canada, October 18 – 20, 2016*.

Qureshi, Sadeem M., Purdy, N., & Neumann, W. P. (2017). Simulating the Impact of Patient Acuity on Nurse Workload and Care Quality. In *Joint proceedings 48th Annual Conference of the Association of Canadian Ergonomists (ACE) & 12th International Symposium on Human Factors in Organizational Design and Management (ODAM), Banff, Canada, July 31 - August 3, 2017* (pp. 232–238).

Qureshi, Sadeem M, Purdy, N., & Neumann, W. P. (2019). *Proceedings of the 20th Congress of the International Ergonomics Association (IEA 2018)* (Vol. 821). Springer International Publishing. https://doi.org/10.1007/978-3-319-96080-7

Qureshi, Sadeem Munawar, Purdy, N., Mohani, A., & Neumann, W. P. (2019). Predicting the effect of Nurse-Patient ratio on Nurse Workload and Care Quality using Discrete Event Simulation. *Journal of Nursing Management*, *27*(5), 971–980. https://doi.org/10.1111/jonm.12757

Reason, J. T. (2004). Beyond the organisational accident: the need for "error wisdom" on the frontline. *Quality & Safety in Health Care*, *13 Suppl 2*, ii28-33. https://doi.org/10.1136/qhc.13.suppl_2.ii28

Recio-saucedo, A., Ora, C. D., Ball, J., Ba, J. B., Meredith, P., Analyst, I., … Ba, P. G. (2018). What impact does nursing care left undone have on patient outcomes ? Review of the literature. *Journal of Clinical Nursing*, (August 2017), 2248–2259. https://doi.org/10.1111/jocn.14058

Registered Nurses Association of Ontario. (2008). Workplace Health, Safety and Well-being of the Nurse. *Healthy Work Environment Best Practice Guidelines*, (February), 1–100.

Reid, P. P., Compton, W. D., Grossman, J. H., & Fanjiang, G. (2005). *Building a Better Delivery Systemm: A New Engineering/Health Care Partnership*. *National Academy of Engineering, Institute of Medicine*. https://doi.org/10.17226/11378

Reiling, J., Hughes, R. G., & Murphy, M. R. (2008). *The Impact of Facility Design on Patient Safety*. *Patient Safety and Quality: An Evidence-Based Handbook for Nurses*. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/21328735

Resnick, D. (2003). The Jesica Santillan Tragedy: Lessons Learned. *Hastings Center Report*, *33*(4), 15–20. https://doi.org/10.2307/3528375

Rhéaume, A., & Mullen, J. (2018). The impact of long work hours and shift work on cognitive errors in nurses. *Journal of Nursing Management*, *26*(1), 26–32. https://doi.org/10.1111/jonm.12513

Rizo-Baeza, M., Mendiola-Infante, S. V., Sepehri, A., Palazón-Bru, A., Gil-Guillén, V. F., & Cortés-Castell, E. (2018). Burnout syndrome in nurses working in palliative care units: An analysis of associated factors. *Journal of Nursing Management*, *26*(1), 19–25. https://doi.org/10.1111/jonm.12506

Robert, J. M., & Brangier, É. (2012). Prospective ergonomics: Origin, goal, and prospects. *Work*, *41*(SUPPL.1), 5235–5242. https://doi.org/10.3233/WOR-2012-0012-5235

Rogers, A. E., Hwang, W.-T., Scott, L. D., Aiken, L. H., & Dinges, D. F. (2004). The Working Hours Of Hospital Staff Nurses And Patient Safety. *Health Affairs*, *23*(4), 202–212. https://doi.org/10.1377/hlthaff.23.4.202

Rogers, B., Buckheit, K., & Ostendorf, J. (2013). Ergonomics and Nursing in Hospital

Environments. *Workplace Health & Safety*, *61*(10), 429–439. https://doi.org/10.1177/216507991306101003

Rosen, K. R. (2008). The history of medical simulation. *Journal of Critical Care*, *23*(2), 157–166. https://doi.org/10.1016/j.jcrc.2007.12.004

Rosenberger, J. M., Green, D. B., Keeling, B., Turpin, P. G., & Zhang, J. M. (2004). Optimizing nurse assignment. *Proceedings of the 16th Annual Society for Health Systems Management Engineering Forum*, (May).

Ruotsalainen, J. H., Verbeek, J. H., Mariné, A., & Serra, C. (2015). *Preventing occupational stress in healthcare workers*. *Cochrane Database of Systematic Reviews*. https://doi.org/https://doi.org/10.1002/14651858.CD002892.pub5

Russ, A. L., Fairbanks, R. J., Karsh, B.-T., Militello, L. G., Saleem, J. J., & Wears, R. L. (2013). The science of human factors: separating fact from fiction. *BMJ Quality & Safety*, *22*(10), 802–808. https://doi.org/10.1136/bmjqs-2012-001450

Sale, J. E. M., Beaton, D. E., Bogoch, E. R., Elliot-Gibson, V., & Frankel, L. (2010). The BMD muddle: The disconnect between bone densitometry results and perception of bone health. *Journal of Clinical Densitometry*, *13*(4), 370–378. https://doi.org/10.1016/j.jocd.2010.07.007

Sargent, R. G. (2013). Verification and validation of simulation models. *Journal of Simulation*, *7*(1), 12–24. https://doi.org/10.1057/jos.2012.20

Schlessinger, L., & Eddy, D. M. (2002). Archimedes: A new model for simulating health care systems - The mathematical formulation. *Journal of Biomedical Informatics*, *35*(1), 37–50. https://doi.org/10.1016/S1532-0464(02)00006-0

Schmidt, R., Geisler, S., & Spreckelsen, C. (2013). Decision support for hospital bed management using adaptable individual length of stay estimations and shared resources. *BMC Medical Informatics and Decision Making*, *13*(1), 1–19. https://doi.org/10.1186/1472-6947-13-3

Schoeller, D. A. (1980). Model for determining the influence of instrumental variations on the long-term precision of isotope dilution analyses. *Biological Mass Spectrometry*, *7*(11–12), 457–463. https://doi.org/10.1002/bms.1200071103

Seo, H. B., Choi, Y. S., & Zimring, C. (2011). Impact of hospital unit design for patient-centered care on nurses' behavior. *Environment and Behavior*, *43*(4), 443–468. https://doi.org/10.1177/0013916510362635

Silas, L. (2015). Creating Safe Cultures and Work Environments for Nurses. In *Quality and Safety Summit: Leveraging Nursing Leadership. November 23 & 24, 2015*. Toronto.

Skår, R. (2010). The meaning of autonomy in nursing practice. *Journal of Clinical Nursing*, *19*(15–16), 2226–2234. https://doi.org/10.1111/j.1365-2702.2009.02804.x

Song, D., Chung, F., Ronayne, M., Ward, B., Yogendran, S., & Sibbick, C. (2004). Fast-tracking (bypassing the PACU) does not reduce nursing workload after ambulatory surgery. *British Journal of Anaesthesia*, *93*(6), 768–774. https://doi.org/10.1093/bja/aeh265

Statistics Canada. (2006). *2005 National Survey of the Work and Health of Nurses*.

Sterman, J. D. (1994). Learning in and about complex systems. *System Dynamics Review*, *10*(2–3), 291–330. https://doi.org/10.1002/sdr.4260100214

Sterman, J. D. (2002). All models are wrong: Reflections on becoming a systems scientist. *System Dynamics Review*, *18*(4), 501–531. https://doi.org/10.1002/sdr.261

Stimpfel, A. W., Sloane, D. M., & Aiken, L. H. (2012). The Longer The Shifts For Hospital Nurses, The Higher The Levels Of Burnout And Patient Dissatisfaction. *Health Affairs*, *31*(11), 2501–2509. https://doi.org/10.1377/hlthaff.2011.1377.The

Storheim, K., & Zwart, J.-A. (2014). Editorial: Musculoskeletal disorders and the Global Burden of Disease study. *Annals of the Rheumatic Diseases*, *73*(6), 949–950. https://doi.org/10.1038/nrrheum.2014.16

Sundaramoorthi, D., Chen, V. C. P., Rosenberger, J. M., Kim, S. B., & Buckley-Behan, D. F. (2009). A data-integrated simulation model to evaluate nurse-patient assignments. *Health Care Management Science*, *12*(3), 252–268. https://doi.org/10.1007/s10729-008-9090-7

Swisher, J. R., & Jacobson, S. H. (2002). Evaluating the Design of a Family Practice Healthcare Clinic Using Discrete-Event Simulation. *Health Care Management Science*, *5*(2), 75–88. https://doi.org/10.1023/A:1014464529565

Tabak, N., Bar-Tal, Y., & Cohen-Mansfield, J. (1996). Clinical Decision Making of Experienced and

Novice Nurses. *Western Journal of Nursing Research*, *18*(5), 534–547.

Takala, E. P., Pehkonen, I., Forsman, M., Hansson, G. Å., Mathiassen, S. E., Neumann, W. P., … Winkel, J. (2010). Systematic evaluation of observational methods assessing biomechanical exposures at work. *Scandinavian Journal of Work, Environment and Health*, *36*(1), 3–24. https://doi.org/10.5271/sjweh.2876

Thinkhamrop, W., Sawaengdee, K., Tangcharoensathien, V., Theerawit, T., Laohasiriwong, W., Saengsuwan, J., & Hurst, C. P. (2017). Burden of musculoskeletal disorders among registered nurses: Evidence from the Thai nurse cohort study. *BMC Nursing*, *16*(1), 1–9. https://doi.org/10.1186/s12912-017-0263-x

Trinkoff, A. M., Lipscomb, J. A., Geiger-Brown, J., Storr, C. L., & Brady, B. A. (2003). Perceived physical demands and reported musculoskeletal problems in registered nurses. *American Journal of Preventive Medicine*, *24*(3), 270–275. https://doi.org/10.1016/S0749-3797(02)00639-6

Trinkoff, A. M., Storr, C. L., & Lipscomb, J. A. (2001). Physically Demanding Work and Inadequate Sleep, Pain Medication Use, and Absenteeism in Registered Nurses. *J Occup Environ Med.*, *43*(4), 355–363. https://doi.org/10.1097/00043764-200104000-00012

Vicente, K. J. (2008). Human factors engineering that makes a difference: Leveraging a science of societal change. *Theoretical Issues in Ergonomics Science*, *9*(1), 1–24. https://doi.org/10.1080/14639220600723484

Village, J., Greig, M., Salustri, F. A., & Neumann, W. P. (2012). Linking human factors to corporate strategy with cognitive mapping techniques. *Work*, *41*(SUPPL.1), 2776–2780. https://doi.org/10.3233/WOR-2012-0523-2776

Walton, M., Woodward, H., Van Staalduinen, S., Lemer, C., Greaves, F., Noble, D., … Barraclough, B. (2010). The WHO patient safety curriculum guide for medical schools. *Quality & Safety in Health Care*, *19*(6), 542–546. https://doi.org/10.1136/qshc.2009.036970

Weigl, M., Müller, A., Angerer, P., & Hoffmann, F. (2014). Workflow interruptions and mental workload in hospital pediatricians: an observational study. *BMC Health Services Research*, *14*(1), 433. https://doi.org/10.1186/1472-6963-14-433

Weissman, J. S., Stern, R., Fielding, S. L., & Epstein, A. M. (1991). Delayed access to health care: Risk factors, reasons, and consequences. *Annals of Internal Medicine*, *114*(4), 325–331. https://doi.org/10.7326/0003-4819-114-4-325

Wells, R., Mathiassen, S. E., Medbo, L., & Winkel, J. (2007). Time-A key issue for musculoskeletal health and manufacturing. *Applied Ergonomics*, *38*(6), 733–744. https://doi.org/10.1016/j.apergo.2006.12.003

Werth, J. (2014). Airborne Weather Radar Limitations. *The Front*, (December). https://doi.org/10.4271/670252

Westgaard, R. H., & Winkel, J. (2011). Occupational musculoskeletal and mental health: Significance of rationalization and opportunities to create sustainable production systems - A systematic review. *Applied Ergonomics*, *42*(2), 261–296. https://doi.org/10.1016/j.apergo.2010.07.002

Winsett, R. P., Rottet, K., Schmitt, A., Wathen, E., & Wilson, D. (2016). Medical surgical nurses describe missed nursing care tasks—Evaluating our work environment. *Applied Nursing Research*, *32*, 128–133. https://doi.org/10.1016/j.apnr.2016.06.006

World Health Organizaiton. (2016). *Global strategic directions for strengthening nursing and midwifery 2016–2020*. Retrieved from https://www.who.int/hrh/nursing_midwifery/global-strategic-midwifery2016-2020.pdf?ua=1

Yi, L., & Seo, H. B. (2012). The effect of hospital unit layout on nurse walking behavior. *Health Environments Research and Design Journal*, *6*(1), 66–82. https://doi.org/10.1177/193758671200600104

Yoder, E. A. (2010). Compassion fatigue in nurses. *Applied Nursing Research*, *23*(4), 191–197. https://doi.org/10.1016/j.apnr.2008.09.003

Zanda, S., Zuddas, P., & Seatzu, C. (2018). Long term nurse scheduling via a decision support system based on linear integer programming: A case study at the University Hospital in Cagliari. *Computers and Industrial Engineering*, *126*(September 2017), 337–347. https://doi.org/10.1016/j.cie.2018.09.027

Zhang, L., Niu, J., Feng, X., Xu, S., Li, X., & Musculo-, Á. H. Á. J. Á. (2013). The 19th International Conference on Industrial Engineering and Engineering Management. *The 19th International Conference on Industrial Engineering and Engineering Management*, (January). https://doi.org/10.1007/978-3-642-38433-2

Zhang, Y., Li, Y., Peng, C., Mou, D., Li, M., & Wang, W. (2018). The height-adaptive parameterized step length measurement method and experiment based on motion parameters. *Sensors (Switzerland)*, *18*(4). https://doi.org/10.3390/s18041039