ANALYTICAL METHODS FOR INTEGRATING STATE-OF-THE-ART HEALTHCARE QUALITY FRAMEWORKS INTO DECISION-MAKING

A Dissertation by

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The following faculty members have examined the final copy of this dissertation for form and content, and recommend that it be accepted in partial fulfillment of the requirement for the degree of Doctor of Philosophy with a major in Industrial Engineering.

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ABSTRACT

In 2001, the Institute of Medicine proposed the use of six quality aims to guide healthcare improvement efforts. These aims specify that healthcare should be effective, efficient, safe, timely, patient-centered, and equitable. Since then, academics, practitioners, and policy-makers have made countless efforts to improve the quality of healthcare systems; however, most of these efforts still focus on a single dimension when measuring a system's performance. This dissertation investigated the integration of the Institute of Medicine quality aims into operational decision-making through the design and evaluation of possible solutions for two problems from different healthcare settings. The first part of this dissertation analyzed and evaluated analytical approaches to integrate simultaneously all six aims of quality into performance assessment of trauma care. A novel multi-criteria approach based on deterministic dominance theory and a traditional single composite approach were analyzed and compared in terms of the categorization of the trauma centers. Based on the results, an approach is proposed to integrate the six quality aims into the performance evaluation of trauma care by adjusting an initial composite to include the aim of equity. The second part of this dissertation analyzed and characterized the short-term inpatient care work planning problem considering the IOM quality aims. This study, proposed an optimization model for the problem considering an optimization criteria consistent with the IOM quality aims. Research opportunities to support the analysis of the inpatient care work planning problem were identified based on the results of the case study. Further, the study proposed a methodology to develop unit-specific practical heuristics for the problem. The results of this two-part study provided insights for decision-makers about the practical challenges and significant benefits of integrating the Institute of Medicine quality aims into operational decision-making in healthcare settings.

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LIST OF ABBREVIATIONS

ACHS	AC/HS blood glucose check
ASCOT	American College of Surgeons Committee on Trauma
AD	Absolute Difference
CI	Confidence intervals
CMS	Centers for Medicare & Medicaid Services
DVT	Deep vein thrombosis prophylaxis
E	Expected mortality
E-WA	Equity-adjusted individual hospital weighted average
E-HQID	Equity-Adjusted HQID
HQID	Hospital Quality Incentive Demonstration
IOM	Institute of Medicine
IQR	Interquartile ranges
ISS	Injury Severity Score
LOS	Hospital length of stay
MTQIP	Michigan Trauma Quality Improvement Program
NLGAP	0–1 generalized assignment problem with nonlinear capacity interactions
NPO	Nothing by mouth
O	Observed number of deaths
O/E	Observed-to-expected
OR	Operations Research
PCA	Patient care assistants

LIST OF ABBREVIATIONS (continued)

QI	Quality indicators
RI	Rand Index
SICWP	Short-term impatient care work planning
SMC	Simple matching coefficient
TAS	Time to acute subdural hematoma evacuation
TC	Trauma center
TCT	Time to CT scan
TIL	Time to ischemic limb treatment
TIN	Tracheal intubation
TQIP	Trauma Quality Improvement Program
US	United States

LIST OF SYMBOLS

a_t	end time of round t
β_j	desired time between tasks in $\mathscr{R}_j$
d_i	due time of task i
E_{qh}	expected value for each aim-metric q^{th} and trauma center h^{th}
e_t	available time within each round t ($e_t < a_t - s_t$ due to allowance)
F_n	nth optimization criterion, when more than one performance metric is used
H	set of trauma centers
h	trauma center ($h \in H$)
$\mathscr{I}$	set of tasks, indexed by i
$\mathscr{J}$	index set of pairs of consecutive frequency-based tasks of the same type
$\mathscr{K}$	set of all patients, indexed by k
$\mathscr{N}$	finite set of evaluation criteria, indexed by n
n_{qh}	number of encounters that were eligible for the intervention(s) associated with the qth quality aim within the hth trauma center
O_{qh}	represent the number of encounters in which the qth aim intervention was received within the hth trauma center
p	P value
p_i	(mean) duration of task i
Q	set of quality aims
q	quality aim ($q \in Q$)
$\mathscr{Q}_h$	hth subset of potentially simultaneous tasks ($\mathscr{Q}_h \subseteq \mathscr{I}, h \in \mathscr{S}$)
$\mathscr{R}_j$	jth pair of consecutive frequency-based tasks of the same type ($\mathscr{R}_j \subseteq \mathscr{I}, j \in \mathscr{J}$)
r	Pearson correlation coefficient

r_i	release time of task i
$\mathscr{S}$	index set of subsets of tasks that can be done simultaneously, if any (i.e., "potentially simultaneous")
s_t	start time of round t
σ_h	time savings from assigning potentially simultaneous tasks in $\mathscr{C}_h$ to round t
$\mathscr{T}$	set of rounds in a shift, indexed by t

CHAPTER 1

INTRODUCTION

1.1 Research Background and Motivation

The quality of health care delivered in the United States has received an increased amount of attention during the last few decades from researchers, practitioners, policymakers, and the general public [1, 2]. Evidence of deficiencies in the quality of health care provided in the United States has been accumulating over the years [3-8]. For instance, Schuster et al. [7] found that there were considerably differences between "the care people should receive and the care they do receive". This finding was evidenced later by the first of two historic landmark reports produced by the Institute of Medicine (IOM) about healthcare in the United States. The first *report "To Err is Human: Building a Safer Health System"* illustrated the deficiencies in the quality of healthcare, e.g., up to 98,000 people die each year from medical errors, and stressed the need to address the safety of patients and the quality of care in order to overcome the system failures [4]. The second report, *"Crossing the Quality Chasm: A New Health System for the 21st Century"* proposed that care should be safe, effective, patient-centered, timely, efficient and equitable [5].

Over the years, the IOM quality aims have been used as a framework in numerous initiatives and efforts to improve the quality of healthcare. Different aspects of healthcare have been addressed by researchers and practitioners in those initiatives and efforts. Some studies limit their scope to specific segments of the population, geographical areas, settings, processes, conditions, subspecialties, and hospital units, among others aspects. Other studies addressed the quality problem from the perspective of either the patient or the provider. Another aspect considered has been the level of decision-making [9], considered in this study only at operational level. Examples of the main aspects addressed by attempts to integrate the six IOM aims into the

quality of healthcare at operational level include: pediatric care [10-11], ambulatory care [12], primary care [13], trauma care [14], pre-hospital emergency medical services [15], hospitals [16], critical access hospitals [17], radiology units [18], medical laboratory testing services [19], medical education [20-22], childbearing women and infants [23], hospital healthcare information technology [24], nurse shortage at hospitals [25], and pain management in the emergency department [26]. These examples are intended to be illustrative rather than comprehensive.

Despite the numerous improvement efforts, slow progress toward these six quality aims has been made [1]. Moreover, most healthcare quality is still evaluated considering one aim at a time. This dissertation studies the integration of the IOM quality aims into operational decision-making through the design and evaluation of possible solutions for two healthcare problems. The study considers problems from different healthcare settings, providing a glimpse of the different challenges faced when the IOM quality aims are included as the integral part of a proposed solution. In the first problem, the integration of all the IOM quality aims in the performance evaluation at the institutional level is studied in a trauma care setting. In the second problem, the use of the IOM quality aims to design and evaluate work strategies for a frontline provider is studied in an inpatient care setting. The characteristics of each problem are summarized in this section and more detail is provided in the following chapters.

The economic burden associated with injuries has concerned different stakeholders, along with the need to improve the quality of trauma care [27]. It has been reported that every year in the United States 214,000 people die from injury, and about 2.8 million people were admitted to a hospital in 2015 due to injuries [28]; which has been linked to high costs. In 2013, the total estimated medical and work loss costs related to injuries was $671 billion [28]. In addition to the economic problem, the quality of trauma care has been reported in urgent need of improvement.

On the other hand, it has been suggested that complex trauma systems present an estimated 2% to 3% error-related deaths [29], and due to their high variability, the estimated preventable deaths in these systems can increase even up to 50% [29-30]. Moreover, the percentage of patients who could not receive recommended care has been reported as high as 50% [31]. In recent years, many efforts have been put in place to overcome these quality deficiencies and high costs. Currently, one of the methods to improve healthcare quality at the institutional level is through external benchmarking. The Trauma Quality Improvement Program (TQIP), an initiative of the American College of Surgeons in the United States, is an example of external benchmarking and self-evaluation in trauma care settings [32-33]. However, most of the current performance evaluations in research and practice focus mainly on one quality aim at a time. The most common quality aim used is effectiveness, which is measured by means of mortality or risk-adjusted mortality rates. [14, 27, 32-36]. Thus, the problem lies in identifying an approach that allows the inclusion of all the IOM quality aims in the evaluation of trauma care quality at the institutional level.

Addressing the problem of how to include all IOM aims in the performance evaluation of trauma centers provides insights about potential improvement and challenges at the broad institutional level. However, this study also intends to investigate the same problem from the narrower perspective of delivering daily care at an actual healthcare site. To that end, this study focuses on the frontline American healthcare worker, who bears much of the burden for the systemic problems this study addresses.

In inpatient care systems, a healthcare worker is a provider who performs a set of simple and complex tasks in a healthcare unit where there is a group of patients [37]. In this context, tasks can be of two types: predictable or unpredictable [38] The short-term inpatient care work planning (SICWP) problem consists of assigning the predictable daily tasks of a healthcare worker to rounds

during a predetermined work period, e.g., a shift. In actual healthcare settings, the SICWP problem needs to be solved in real time by healthcare workers during the first few minutes of their workday and adjusted, if necessary, during the rest of the shift. In addition, the variability of each workday and various levels of workload increase the difficulty for the healthcare worker, which can have a negative effect on the well-being of healthcare workers as well as on worker's performance. For example, workers can experience an increase in their stress levels, leading to burnout in the long term [39-40]. Among other effects of inefficient planning are increased potential for errors, inefficiency, worker frustration, and operating costs [41]. Thus, there is a need to identify strategies to support these workers in planning their daily work in order to improve their performance, while considering the IOM aims as a quality framework to design and evaluate the work planning strategies.

The following sections of this chapter present the organization of the dissertation and a summary of the chapters.

1.2 Summary of Chapters

Chapter 2: Incorporating the Six Aims for Quality in the Analysis of Trauma Care

In this study, two analytical approaches were implemented and evaluated, incorporating all the IOM aims into the evaluation of trauma care quality. The first approach consisted of a multivariate quality analysis based on deterministic dominance theory. Trauma centers' performance was determined based on their relationship to the efficient frontier. This approach was compared with a single composite score constructed based on the Individual Hospital Weighted Average method. Both approaches were compared in terms of the categorizations of the trauma centers in an external benchmarking scenario. Based on the results, the second approach was selected to perform a more detailed study of the integration of the IOM quality aims in the

performance evaluation of trauma centers. Two single composites were constructed based on the Individual Hospital Weighted Average method and the Centers for Medicare & Medicaid Services Hospital Quality Incentive Demonstration method. An initial composite included the effectiveness, efficiency, timeliness, and safety aims in both methods, which was adjusted to include the aim of equity as a function of the minimum performance for specific groups. The approaches were compared in terms of the categorization of the trauma centers in two different scenarios: an external benchmarking and a pay-for-performance program. The results of this comparison provide insights into the data preprocessing each approach requires and help reveal the most significant underlying factors affecting the final results of each approach. This chapter contributes to the current literature by developing an approach to incorporate the IOM aims into the evaluation of trauma care quality.

Chapter 3: Modeling and Analysis of Short-Term Work Planning in Inpatient Care Settings

Chapter 3 investigates inpatient care work planning decisions from the perspective of a single healthcare provider in a hospital unit. It characterizes short-term work planning decisions made by frontline inpatient care workers and illustrates how operations research (OR) can support the analysis of such decisions. A classification of inpatient care tasks was proposed based on the literature findings and information collected from the observation of healthcare providers in an inpatient care unit. An optimization model based on the 0–1 generalized assignment problem with nonlinear capacity constraints was proposed to model the short-term work planning decisions. Optimization criteria consistent with the IOM quality aims were identified. Data from an inpatient care hospital unit was used to obtain optimal solutions for the case study. Based on the analysis of optimal solutions, trade-offs between the operational off-line performance metrics for the inpatient care unit were identified. The results provided insights to support healthcare providers in

identifying work plans that allow them to care for their patients in a safe, timely, efficient, effective, patient-centered and equitable manner. Furthermore, research opportunities to support the analysis of the inpatient care work planning problem were identified based on the results of the case study.

Chapter 4: Developing Practical Context-Based Work Planning Strategies for Inpatient Care

Chapter 4 investigates the SICWP problem to identify context-based work planning strategies that healthcare workers can apply without computational resources additional to those used in current practice. A methodology to develop unit-specific practical heuristics for inpatient care workers to solve the SICWP problem is proposed and illustrated using actual work execution data from a collaborating hospital unit. Optimal solutions obtained using the model and optimization criteria developed in Chapter 3 are analyzed using association analysis to identify patterns related to task-to-round for a set of baseline scenarios. The practical heuristic for the hospital unit is constructed based on identified frequently occurring patterns and compared with the status quo approach in terms of cognitive complexity. The practical heuristic is also compared with the optimal and status quo approaches in terms of the unit-specific quality metrics, which are consistent with the IOM aims. Results show that the healthcare worker could experience more cognitive workload using the practical heuristic, but it could still be used without additional computational resources. Additionally, results of the Monte Carlo simulation show that the practical heuristic could improve the quality of the provider's work. The proposed methodology can be applied to any inpatient care unit possessing data with similar characteristics to those in the SICWP problem. Moreover, the proposed methodology could potentially be extended to problems from other settings with similar dynamics.

1.3 Organization of Dissertation

The remainder of this dissertation manuscript is organized as follows: Chapter 2 presents a novel multi-criteria approach and a traditional single composite approach to incorporating the IOM aims into the evaluation of trauma care quality. Chapter 3 proposes an optimization model for the SICWP problem that includes evaluation criteria consistent with the IOM quality aims and serves as a framework to identify opportunities to improve inpatient care work. Chapter 4 proposes a methodology that identifies patterns in optimal solutions for the SICWP problem to develop unit-specific practical heuristics. Finally, conclusions and future research directions are discussed in Chapter 5.

CHAPTER 2

INCORPORATING THE SIX AIMS FOR QUALITY IN THE ANALYSIS OF TRAUMA CARE

2.1. Background

Since the quality of US healthcare was reported lower than expected [1, 2], the efforts to improve quality and reduce costs have increased considerably. US trauma care quality has also been reported below expectations over the years, as evidenced by high costs related to medical treatment and lost productivity [3], as well as preventable medical errors with their related deaths [4, 5] Moreover, in 2013 it was reported that more than 3 million people with injuries were admitted to a hospital and more than 192,000 of them died [6]. Therefore, there is an imperative need to improve the quality of trauma care.

Incentive programs and external benchmarking are some of the most common efforts to improve the quality of healthcare in the US [1, 7] In the US, the Trauma Quality Improvement Program (TQIP) is an initiative of the American College of Surgeons (ACS) to improve the quality of trauma care [8] through external benchmarking and self-evaluation [9]. The Premier Hospital Quality Incentive Demonstration (HQID) project, for example, is a pay-for-performance program from the Centers for Medicare & Medicaid Services (CMS) that offers financial incentives to improve the quality of care in hospitals [10].

The Institute of Medicine (IOM) proposed the following six dimensions to guide improvement efforts in healthcare: effectiveness, efficiency, safety, timeliness, equity, and patient-centeredness [2]. Nevertheless, progress toward using all six dimensions to improve the quality of patient care has not gone far enough [7] For trauma care in particular, most published quality assessment and benchmarking studies focus mainly on one aim of quality at a time. Most recent

studies use mortality or risk adjusted mortality rates [8, 9, 11-15] which are measures of effectiveness [14] Some other studies have evaluated length of stay (LOS) [12, 13, 16 -18] which has been associated with efficiency [19]. Besides mortality and LOS, thousands of quality indicators (QIs) either have been proposed or used to assess trauma care [5, 13] However, most of those QIs lack evidence to support them or are not considered reliable or valid [5, 13] Nevertheless, a trauma care study proposed 19 hospital QIs with documented content validity [14]. Those QIs were classified according the IOM aims; however, the study did not include QIs at hospital level along the equity and patient-centeredness aims. In fact, the aims of equity and patient-centeredness are often underrepresented in the trauma care performance literature when compared to the other aims.

While patient-centeredness is difficult to measure given the lack of documented information on patients' preferences at hospital level, equity can be measured by calculating disparities in any metric. Most studies on health disparities are found in the public health domain, where a disparity is generally measured as a function of the difference between the values of a selected QI for disadvantaged and advantaged groups [20]. Although there is still a lack of consensus about the factors that should be considered to assess equity in trauma care [21], socioeconomic characteristics and racial/ethnic disparities have been associated frequently with differences in treatment, outcomes, and access to trauma care [22-24].

In healthcare domains other than trauma, a common approach to perform a multidimensional analysis of performance is to use a composite score that combines more than one QI (e.g. The CMS HQID method) [10, 25-29]. In trauma care settings, Willis et al. [30] concluded that two denominator-based weight composite approaches and an approach based on

principle components analysis demonstrated construct validity; these approaches can therefore be useful in evaluating quality at an institutional level with more than one QI.

The goal of this research was to investigate how to incorporate the IOM aims into the evaluation of trauma care quality. We identified and calculated measures per each quality aim using data from the Michigan TQIP (MTQIP). The study used a multivariate analysis based on deterministic dominance theory [31, 32] to evaluate trauma care quality considering the IOM aims. Also, the study used two composite methods to integrate the aim-measures into a single measure: the Individual Hospital Weighted Average method [30, 33] and the HQID method [10, 26]. The first composite method was selected because it has been validated for trauma care [30, 33] and can provide a three-way categorization similar to that of the traditional mortality analysis, even though it requires some transformation of the original metrics, particularly the O/E mortality ratio. The second composite method was selected because it allows the inclusion of the O/E mortality ratio in its original form. We then compared these methods in terms of their data preprocessing needs, outputs, and implications for trauma centers (TCs) and payers.

2.2 Methods

2.2.1. Data

This study used data from the MTQIP database which, as of 2015, included patients admitted to 27 Level 1 TCs. The analysis focused on patients (age ≥ 18) admitted from 2012 to 2014 with an injury mechanism classified as either blunt or penetrating, Injury Severity Score (ISS) ≥ 5, and Hospital LOS ≥ 1 day. Patients who had no signs of life or were dead on arrival were excluded. Also incomplete records, those with empty values in the fields used in the QI calculations, were excluded. In order to prevent a hospital's identity from being connected with

the results obtained in this study, the data was de-identified before analysis by randomly replacing the TCs' identification number with letters.

2.2.2. Quality Indicators per Aim

Out of the 19 QIs proposed by Santana et al. [14] the dataset allowed for the calculation of 5. These included one indicator within effectiveness (observed-to-expected (O/E) mortality ratio), three indicators associated with timeliness (time to CT scan (TCT)), time to acute subdural hematoma evacuation (TAS), and time to ischemic limb treatment (TIL)), and one indicator representing safety (tracheal intubation (TIN)). Since LOS is one of the most common QIs currently used to evaluate trauma care and has been associated to efficiency, it was selected to represent this aim [19]. Equity was measured using absolute difference (AD) [34, 35] a QI commonly used to assess health inequalities [20, 35]. No QIs or measures of patient-centeredness that could be calculated using the data were identified. Thus, patient-centeredness was not included in this study.

The following are specific considerations of the implementation of the metrics for this study:

- Expected mortality (E) was calculated based on a multivariate logistic regression analysis [11]. Age, sex, and ISS, among other patient level covariates, were used to risk adjust.
- The AD metric was calculated as a function of the difference between the two groups' values of LOS. LOS was selected instead of the O/E mortality ratio because it allowed the analysis of fifteen TCs instead of only eight. The groups were determined using race/ethnicity [21, 36, 37]. In particular, groups of white and black patients were compared in the analysis because they had the highest relative

participation in the dataset (86% and 9%, respectively). Patients of all other racial/ethnic groups (Asian, Native Hawaiian or other Pacific Islander, American Indian, Hispanic, other race) each represented less than 2% of the data.

2.2.3. Single-Aim Analysis

We analyzed the performance of TCs along each aim using caterpillar graphs, which are traditionally used by studies focusing on mortality [11, 15]. In a caterpillar graph, the centerline is calculated based on an estimator of the expected value of the measure being evaluated. The categorization using the caterpillar graphs considers: a low-performing TC has an upper confidence bound lower than the centerline, an average-performing TC has a confidence interval overlapping with the centerline, and a high-performing TC has a lower confidence bound greater than the centerline [11].

For the aim of effectiveness, we used the O/E mortality ratio and calculated its 95% CI using the method proposed by Ury and Wiggins [38]. To study the performance along the aim of efficiency, measured through LOS, the central line and interval bounds were estimated using the median and interquartile ranges (IQR), respectively [17]. The reason is because LOS is not necessarily normally distributed.

The analysis of the aim of timeliness involved more than one QI. Therefore, we first analyzed the available QIs for correlation to avoid redundancy using Pearson correlation coefficient (r). Then, a metric was constructed to assess timeliness by combining its available independent QIs through the Individual Hospital Weighted Average method [30, 33]. The method requires QIs in a ratio form in which the denominator represents the patients who are eligible for the intervention and the numerator represents the patients who actually received the intervention

[33]. However, TAS and TIL are defined in units of time from an initial event until the procedure was performed. Thus, these two QIs were transformed into a ratio using the 4-hour threshold recommended by the ACS Committee on Trauma [39] and an expert panel [14] for TAS and TIL, respectively. The centerline was calculated using the overall timeliness metric of all TCs combined. The confidence bounds were calculated using a 95% CI based on normal approximation of the binomial distribution.

For the aim of safety, we used TIN. Since TIN was also a ratio indicator, its confidence bounds and centerlines were calculated similarly to those of the timeliness metric.

To study the performance along the aim of equity, the 95% CI of AD was calculated based on the method specified by Chen et al. [34] and the centerline was calculated as the average of AD.

2.2.4. Multi-Aim Analysis

2.2.4.1. Multivariate Quality Analysis Based on Deterministic Dominance Theory

The study used deterministic dominance theory to overcome the heterogeneity of quality metrics in evaluating trauma care performance. The approach used the concept of the efficient frontier of a set of alternatives, which is defined as the image (in the outcome space) of the subset of alternatives that include only alternatives that are not dominated by another alternative (i.e., nondominated alternatives) [31]. The approach considered trauma centers as alternatives and aim-metrics as attributes. In this study, a trauma center TC1, dominates another trauma center TC2, if and only if TC1 does at least as well as TC2 on all aim-metrics, and it is better at least in one aim-metric [31, 40] Trauma centers in the efficient frontier were categorized as high performers. In order to identify low performers, a similar approach was used but considering the negative of each

aim-metric in the analysis (i.e., anti-efficient frontier). Trauma centers that were dominated in both analyses were categorized as average performers.

2.2.4.2. Single Composite Score

Two composite methods that can allow for the inclusion of more than one aim into the analysis of trauma care performance were identified and evaluated. These methods were based on the Individual Hospital Weighted Average method [33, 30] and the HQID method [10, 26] respectively.

In the equity-adjusted Individual Hospital Weighted Average (E-WA) O/E method, all aim-metrics were calculated or transformed so that higher values could denote good performance [40] Particularly for effectiveness, we used survival rate instead of mortality rate, which represents the ratio of patients who survived (1- observed deaths) [26] divided by the total number of patients. In addition, all the aim-metrics, except equity, were included in the composite as ratios. LOS, originally defined in days, was transformed into a ratio using the threshold defined by the median LOS when considering data for all TCs. The equity metric could not be transformed to a ratio-type indicator. Therefore, we incorporated equity into the analysis by adjusting the composite obtained from all the other available aims.

The E-WA O/E composite per each TC was calculated as shown in equation (1), where $WA\ O/E\ Comp_{hs}$ is the individual hospital weighted average composite calculated for trauma center h^{th} ($h \in H$) and for the sth group of interest ($s \in S/all$) required for the equity adjustment. In this study, $H = \{A, B, C, \ldots, P\}$ and $S = \{black, white, all\}$. The group "all" represents full set of patients.

To adjust for equity, equation (1) calculates the composite as follows. For each TC, composites along with their CIs are calculated separately for two or more groups of interest related

to the equity aim (e.g. black and white patients). The CIs are used to determine if the difference between groups' performance is significant or not. If one of the two groups have a significantly lower composite value, then that lower value is used to represent the performance of the corresponding TC. If there is no significant difference in the composite values between the two groups considered, then the composite value for all patients regardless of their group (e.g. all races) is used as the performance measure for the TC.

The composite $WA\ O/E\ Comp_{hs}$ was calculated as shown in equation (2), where $OComp_{hs}$ is the proportion of encounters in which the corresponding quality interventions associated with the aims included in the analysis are observed and $EComp_{hs}$ is the proportion of encounters in which the corresponding quality interventions associated with the same aims are expected. These observed and expected values were calculated as shown in equations (3) and (4), respectively, where n_{qhs} represent the number of encounters that are eligible for the intervention(s) associated with the qth quality aim ($q \in Q$) in the hth trauma center ($h \in H$) for the sth group ($s \in S$). O_{qhs} represent the number of encounters in which the qth aim intervention is received within the hth trauma center for the sth group ($s \in S$). In this study, $Q = \{effectiveness, efficiency, timeliness, safety\}$. E_{qhs} is the expected number of encounters in which the qth aim intervention should have been received within the hth trauma center for the sth group. For all aims except the effectiveness and equity aims, E_{qhs} was calculated by multiplying the overall ratio by n_{qhs} as shown in equation (5). The expected value for the survival rate ($E_{Effectiveness,h}$) was calculated as the expected survival rate (1- Expected deaths), where expected deaths was calculated as the expected mortality (E) multiplied by $n_{effectiveness,h}$.

The 95 % CI for the E-WA O/E method was calculated using the method proposed by Ury and Wiggins [38].

The equity-adjusted HQID (E-HQID) composite was calculated using a similar approach to the one used in the E-WA O/E method. We first calculated the HQID composite for all groups in addition to the composite for each specific group of interest. Then we selected the measure based on the presence of significant differences as shown in equation (6).

The HQID composite has two components as shown in equation (7). The first component corresponds to the effectiveness aim (survival rate) and the second component combines the metrics for the aims of safety, timeliness, and efficiency. Each component is weighted by the number of aims in each component divided by the total number of aims considered [30, 33].

Since the distributional properties of the E-HQID composite were unknown, the CIs were calculated using bootstrap resampling based on percentiles. The composite for each TC was computed from 1,000 bootstrap samples per aim-metric [41, 42]. The centerline is considered the overall E-HQID composite for all TCs.

$$E\text{-}WA\ O/E\ Comp_h = \begin{cases} \min\limits_{S/\{all\}} \{WA\ O/E\ Comp_{hs}\} & \text{if significantly different,} \\ WA\ O/E\ Comp_{hs=all} & \text{otherwise} \end{cases} \quad \forall\ h\ in\ H, \tag{1}$$

$$WA\ O/E\ Comp_{hs} = \frac{OComp_{hs}}{EComp_{hs}}\ \forall\ h\ in\ H, \forall\ s \in S, \tag{2}$$

$$OComp_{hs} = \frac{\sum_{q \in Q} O_{qhs}}{\sum_{q \in Q} n_{qhs}}\ \forall\ h\ in\ H, \forall\ s \in S, \tag{3}$$

$$EComp_{hs} = \frac{\sum_{q \in Q} E_{qhs}}{\sum_{q \in Q} n_{qhs}}\ \forall\ h\ in\ H, \forall\ s \in S, \tag{4}$$

$$E_{qhs} = \left(\frac{\sum_{h \in H} O_{qhs}}{\sum_{h \in H} n_{qhs}}\right) n_{qhs} \forall\ q\ in\ Q, \forall\ s \in S, \tag{5}$$

$$E\text{-}HQID\ Comp_h = \begin{cases} \min\limits_{S/\{all\}} \{HQID\ Comp_{hs}\} & \text{if significantly different,} \\ HQID\ Comp_{hs=all} & \text{otherwise} \end{cases} \quad \forall\ h\ in\ H, \tag{6}$$

$$HQID\ Comp_{hs} = \left(\frac{1}{4}\right)\left(\frac{O_{effectivenes,hs}}{E_{effectiveness,hs}}\right) + \left(\frac{3}{4}\right)\left(\frac{\sum_{q\in Q/\{effectivenes\}} O_{qhs}}{\sum_{q\in Q/\{effectivenes\}} n_{qhs}}\right) \ \forall\ h \in\ H, \forall\ s \in S. \quad (7)$$

By definition, both methods are equivalent to a weighted average of the original aim-metrics included. In each composite, those weights depend not only on the form of the metric, but also on the data composition. In the E-WA O/E method, the weight of the effectiveness aim is given by the ratio of $E_{Effectiveness,h}$ divided by the sum of E_{qhs} corresponding to all q^{th} quality aims including effectiveness. In the same method, the weight of each of the remaining original aim-metrics is given by the ratio of the corresponding n_{qhs} divided by the sum of E_{qhs} over all quality aims, including effectiveness. In the E-HQID method, the weight of the effectiveness aim is fixed at one-fourth when including the same number of aims as included in this study. In general, the weight for effectiveness in this approach is given by $1 / (\| Q \| - 1)$. In the same method, the weight of each remaining original aim-metric is given by three-fourths of the ratio of the corresponding n_{qhs} divided by the sum of n_{qhs} corresponding to all the quality aims except effectiveness.

The relationship between the original aim-metrics and the composites themselves were analyzed using the Pearson correlation coefficient (r). In addition, the degree of agreement between the resulting TC categorizations for the different methods studied was analyzed using the Rand Index (RI) [43, 44]. The degree of agreement regarding RI considered: < 0.2 poor, < 0.4 fair, < 0.6 moderate, < 0.8 good, ≥ 0.8 to 1 very good; similar to the guidelines used for a common inter-agreement coefficient [45]. Also, the multi-aim methods were compared using an incentive program based on the CMS HQID project [10] and the relationships of the weights allocated to each aim.

2.3. Results

The dataset used to perform the comparisons included 16 TCs and 24,794 patients who met the inclusion criteria. Approximately half of the patients in the dataset were younger than 65 years

(53%), and approximately half were male patients (53%). Most of the patients in the dataset presented blunt injury (99%) and a small percentage of patients in the dataset had an ISS ≥ 25 (6%).

2.3.1. Single-Aim Analysis

Correlation coefficients were low or moderate for all pairs of aim-metrics in all years ($r < \pm 0.51$), but non-significant linear correlations were found (significance level of 0.01). Thus, we conclude that combining all aims could add value to the analysis. Figures 2.1 and 2.2 illustrate the single-aim analyses using data from 2014. Effectiveness and efficiency resulted in all centers considered average performers. Even though effectiveness resulted in a categorization identical to efficiency and equity (RI = 1), its categorization was different from safety (RI = 0.76, good agreement) and timeliness (RI = 0.29, fair agreement). These results were approximately similar to the other years of analysis except for effectiveness-efficiency and effectiveness-equity. In 2012 and 2013, effectiveness' categorizations showed moderate agreement with efficiency and equity (RI: 0.40 - 0.59).

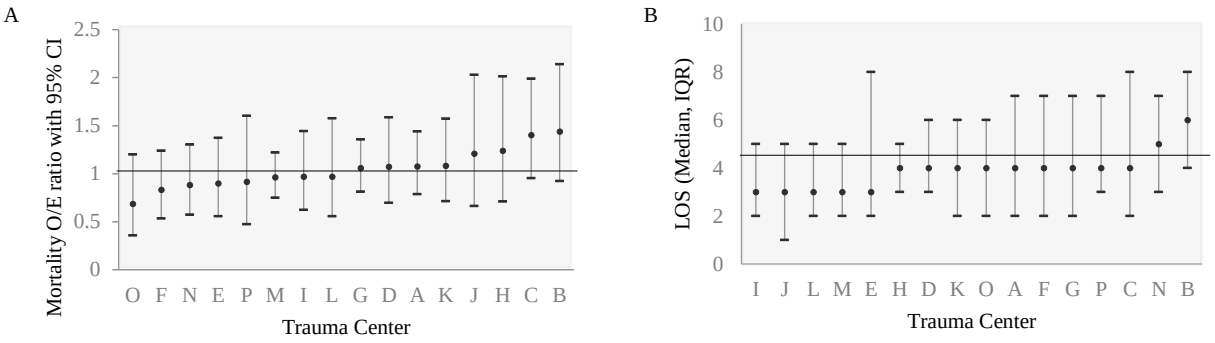

Figure 2.1. A, Caterpillar graph of Mortality O/E ratios with 95% CIs. B, Caterpillar graph of LOS with IQRs and median. All centers are considered average performers in A and B.

2.3.2. Multi-Aim Analysis

Multivariate quality analysis based on the deterministic theory was used to identify trauma centers in the efficient frontier. Four aims were analyzed: effectiveness, efficiency, safety, and timeliness (see Figure 2.3). Similarly, the trauma centers in the anti-efficient frontier were identified using the same method but for the negative of each aim-metric. Using the proposed methodology, trauma centers were categorized as high performers (E, I, J, K, D, O, M, and N), average performers (C, F, G, H, L, and P), and low performers (A and B) (see Figure 2.4).

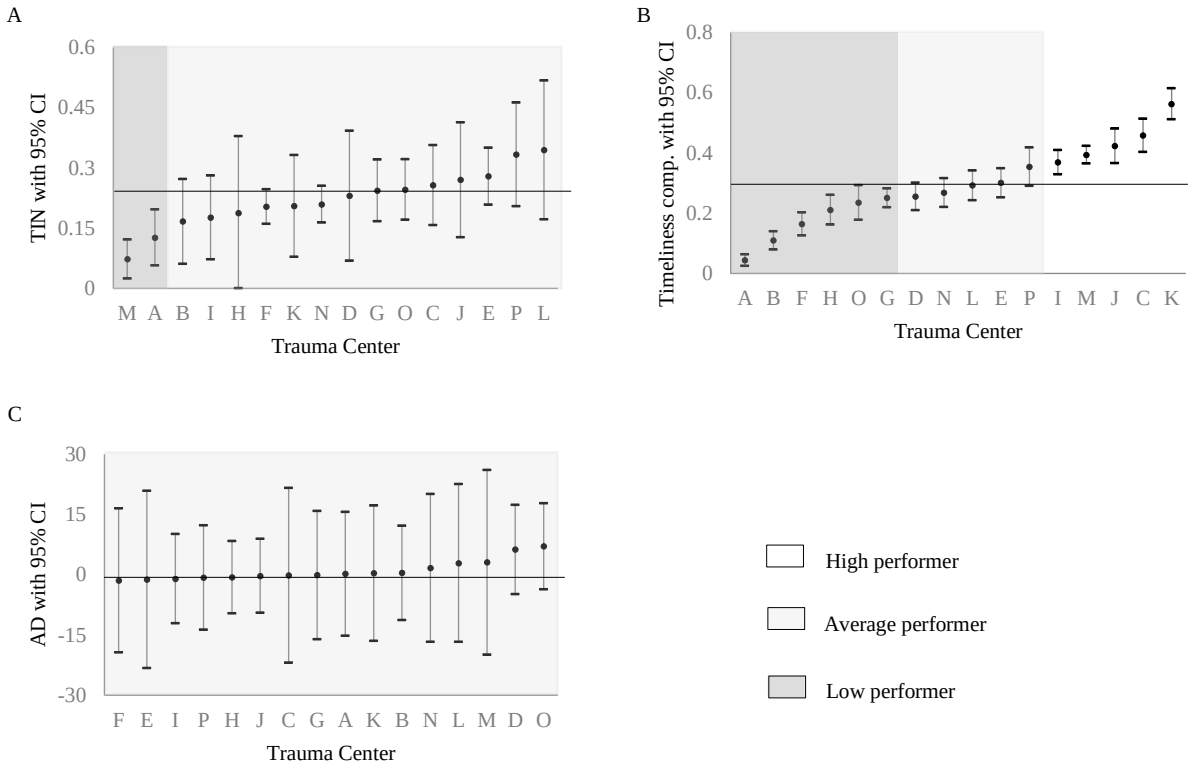

Figure 2.2. A, Caterpillar graph of TIN with 95% CIs. B, Caterpillar graph of Timeliness composite with 95% CIs. C, Caterpillar graph of AD with 95 % CIs.

Using the E-WA O/E method, TCs were distributed over the three categories in each year of analysis. For example, out of the 16 TCs analyzed in 2014, two were categorized as low performers, nine as average performers, and five as high performers (Fig. 2.5 *A*). The E-WA O/E

method categorization had the highest agreement with timeliness (2013 and 2014: RI = 0.63) and safety (2012: RI = 0.61), and had decreasing agreement with the effectiveness, efficiency, and equity aims in all years (RI < 0.48).

The results indicated good agreement between the multivariate quality analysis based on the deterministic dominance theory and the single composite based on the Individual Hospital Weighted Average method (RI=0.791).

The E-HQID method resulted in three categories in each year of analysis. For example, in 2014, five TCs were categorized as low performers, five as average performers, and six as high performers (Fig. 2.5 *B*). This categorization was most consistent with timeliness (2014: RI = 0.71; 2013: RI = 0.72; 2012: RI = 0.67) and least consistent with the effectiveness, efficiency, and equity aims in all years (RI < 0.48).

The E-WA O/E and the E-HQID composite scores demonstrated moderate positive correlation (r = 0.51, p = 0.044) as well as good agreement between the corresponding categorizations in all years of analysis (2014: RI = 0.71; 2013: RI = 0.80; 2012: RI = 0.79). A summary of the categorizations resulting from single and composite measures for 2014, sorted by TC, can be found on Table 2.1.

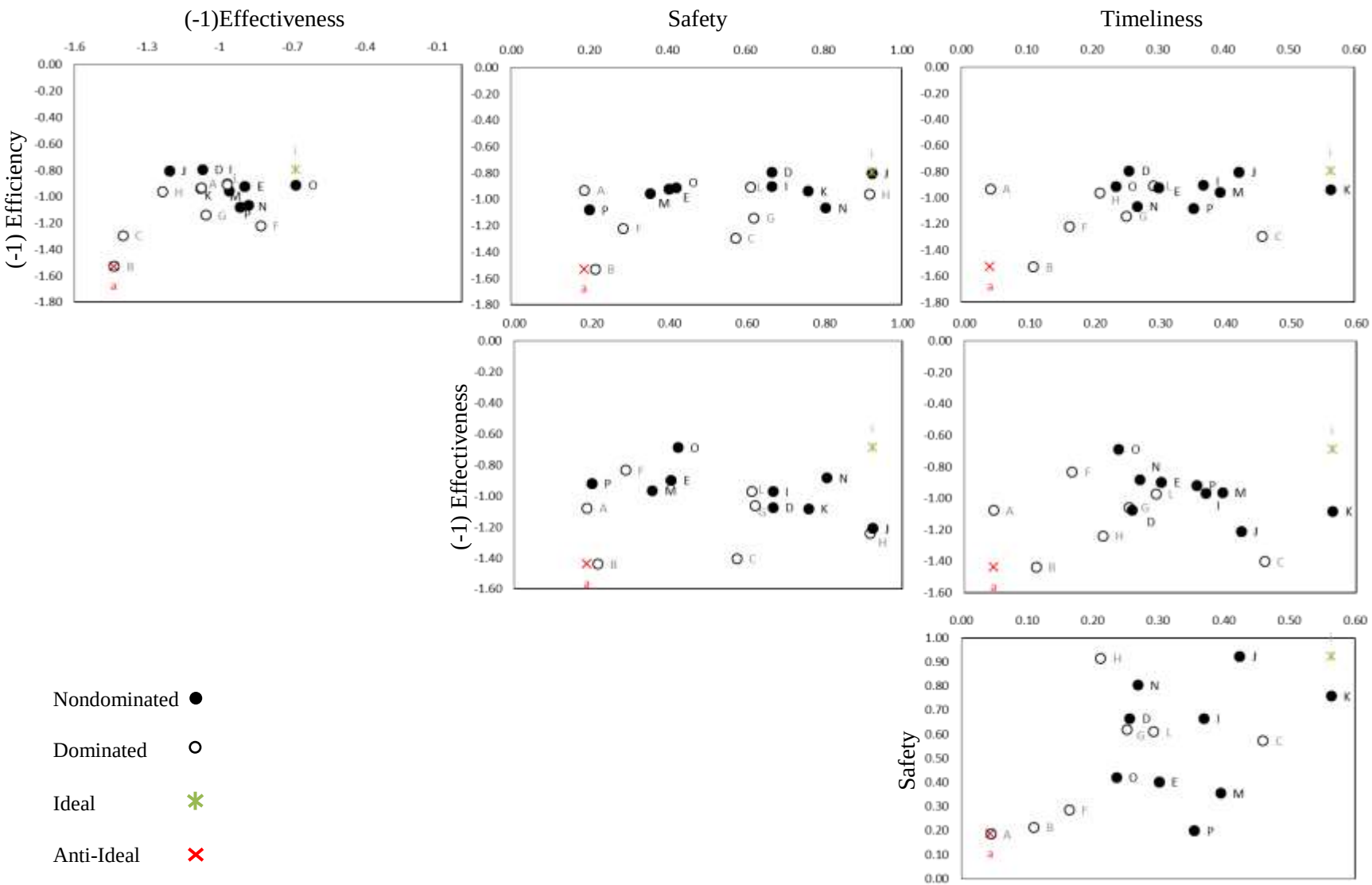

Figure 2.3: Efficient frontier graph from the multivariate quality analysis based on deterministic dominance theory.

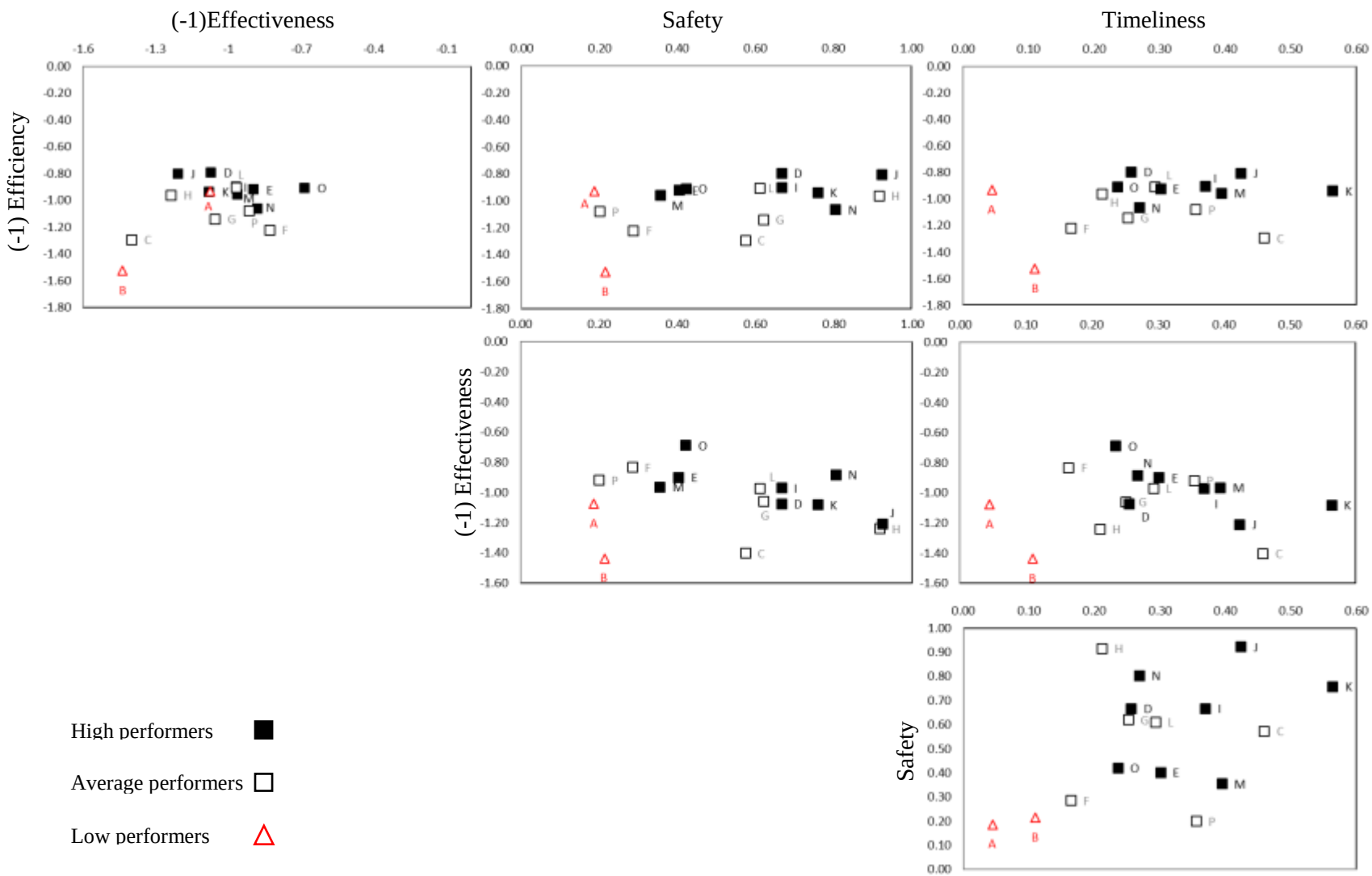

Figure 2.4: Performance categorization of trauma centers from the multivariate quality analysis based on deterministic dominance theory.

The comparison in relation to an incentive program showed that the E-WA O/E and E-HQID methods could have different monetary impact for some TCs over a three-year analysis, assuming a fixed annual payment of $100 per TC per year (Table 2.2). Three (20.0%) TCs received incentives regardless of the multi-aim method, but only one (6.6%) received the same amount. Similarly, two (13.3%) TCs received penalties regardless of the multi-aim method, but only one (6.6%) received the same amount. The use of the effectiveness metric for the incentive program resulted in more and mostly different TCs penalized in relation to any of the multi-aim methods. One (6.6%) TC received the same amount in incentives as the E-WA O/E method and one (6.6%) TC received the same amount in penalties as the E-HQID method. The payer had different overall expenditures for the different multi-aim methods considered. However, using effectiveness only to guide performance evaluation resulted in savings to the payer.

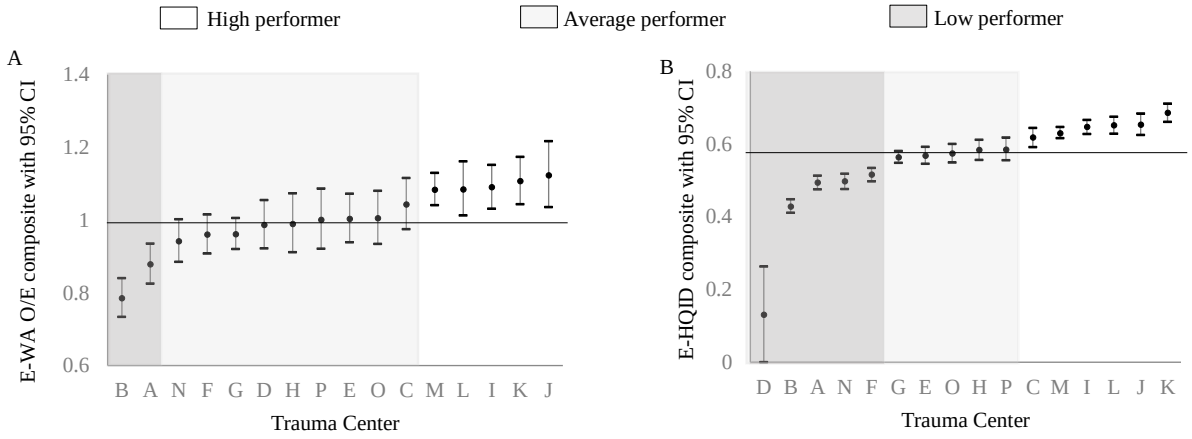

Figure 2.5. A, Caterpillar graph of the E-WA O/E composite method with 95% CI. B, Caterpillar graph of E-HQID composite method.

The comparison in relation to the weights allocated to each aim indicated that in the E-WA O/E method, the effectiveness and efficiency aims had similar weights in all years of analysis (the efficiency weight was 101.5% of the effectiveness weight with a standard deviation (SD) of 6.1%), but those weights were consistently higher than the weights given to the timeliness and safety aims.

The safety aim had similar weight in all years (17.6% of the effectiveness weight with a SD of 1.3%). The timeliness weight was similar in 2013 and 2014 (72.0% of the effectiveness weight with a SD of 0.7%) but smaller in 2012 (6.6% of the effectiveness weight). The E-HQID method, on the other hand, tended to give the highest weight to efficiency (158.3% of the effectiveness weight with a SD of 5.6%) and timeliness (113.9% of the effectiveness weight with a SD of 5.8%) in 2013 and 2014. The safety aim had smaller but similar weight in all years (30.9% of the effectiveness weight with a SD of 4.4%). The weights for efficiency and timeliness were different in 2012 (247.6% and 15.1% of the effectiveness weight, respectively) than other years due to variations in the data composition.

TABLE 2.1.

PERFORMANCE RESULTS, SINGLE-AIM AND MULTIPLE-AIM APPROACHES

TC†	Effectiveness	Efficiency	Safety	Timeliness	Equity	Multivariate quality analysis	E-WA O/E composite	E-HQID composite
A	AVERAGE	AVERAGE	LOW	LOW	AVERAGE	LOW	LOW	LOW
B	AVERAGE	AVERAGE	AVERAGE	LOW	AVERAGE	LOW	LOW	LOW
C	AVERAGE	AVERAGE	AVERAGE	HIGH	AVERAGE	AVERAGE	AVERAGE	HIGH
D	AVERAGE	AVERAGE	AVERAGE	AVERAGE	AVERAGE	HIGH	AVERAGE	LOW
E	AVERAGE	AVERAGE	AVERAGE	AVERAGE	AVERAGE	HIGH	AVERAGE	AVERAGE
F	AVERAGE	AVERAGE	AVERAGE	LOW	AVERAGE	AVERAGE	AVERAGE	LOW
G	AVERAGE	AVERAGE	AVERAGE	LOW	AVERAGE	AVERAGE	AVERAGE	AVERAGE
H	AVERAGE	AVERAGE	AVERAGE	LOW	AVERAGE	AVERAGE	AVERAGE	AVERAGE
I	AVERAGE	AVERAGE	AVERAGE	HIGH	AVERAGE	HIGH	HIGH	HIGH
J	AVERAGE	AVERAGE	AVERAGE	HIGH	AVERAGE	HIGH	HIGH	HIGH
K	AVERAGE	AVERAGE	AVERAGE	HIGH	AVERAGE	HIGH	HIGH	HIGH
L	AVERAGE	AVERAGE	AVERAGE	AVERAGE	AVERAGE	AVERAGE	HIGH	HIGH
M	AVERAGE	AVERAGE	LOW	HIGH	AVERAGE	HIGH	HIGH	HIGH
N	AVERAGE	AVERAGE	AVERAGE	AVERAGE	AVERAGE	HIGH	AVERAGE	LOW
O	AVERAGE	AVERAGE	AVERAGE	LOW	AVERAGE	HIGH	AVERAGE	AVERAGE
P	AVERAGE	AVERAGE	AVERAGE	AVERAGE	AVERAGE	AVERAGE	AVERAGE	AVERAGE

†TC: trauma center

TABLE 2.2.

INCENTIVE (PENALTY) FOR TRAUMA CENTERS AND PAYER FOR A PERIOD OF THREE YEARS OF ANALYSIS (VALUES IN $100)

	Trauma center															Payer
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	P	
Effectiveness	2	(1)	(2)	(2)	0	2	0	(2)	2	(2)	(2)	(1)	1	2	(1)	4
E-WA O/E	(1)	(2)	0	0	0	0	1	0	1	6	6	0	1	0	0	(12)
E-HQID	(1)	(2)	0	(2)	0	0	4	0	0	4	6	1	0	(1)	0	(9)

2.4 Discussion

According to the IOM, integrating all quality aims into trauma care performance evaluation inherently provides a better representation of the multidimensional nature of healthcare quality, regardless of the method used. Each multi-aim method produced different categorizations of the TCs than those categorizations obtained using the corresponding single-aim analyses. These differences illustrated the potential gain of information when incorporating multiple dimensions into the analysis and confirm previous findings indicating that only one outcome may not be sufficient to assess the performance of TCs [5, 11, 46].

The multivariate quality analysis based on deterministic dominance theory and single composite based on the Individual Hospital Weighted Average method produced different categorizations of trauma centers. Although the single composite approach required metrics in ratio form, which can be considered a limitation, this approach is based on traditional statistical methods (e.g. mortality analysis). On the other hand, the deterministic dominance theory approach did not present requirements related to the metrics' type. However, the multivariate approach could present a significant challenge for the intended user's acceptance. As an attempt to overcome this challenge, the study considered the possibility of modifying the method used to determine the performance categories of trauma centers to resemble the traditional approach more closely.

However, the attempt did not succeed, because whenever aim-metrics' confidence intervals (CIs) were included in the analysis, the method could not be used in some cases. For instance, some TCs were categorized as high and low performers simultaneously due to the relatively high variability of at least one aim-metric, which was observed in the aim-metric's confidence interval (CI) magnitude. Therefore, the single composite approach was selected to perform a more detailed analysis of the integration of all the IOM quality aims into the performance evaluation of trauma centers.

The two multi-aim approaches evaluated resulted in different categorizations of the TCs, even though they considered the same aims and QIs. Such differences were mainly due to the weights given to each aim by the composite method itself along with the dataset composition. The relationships between weights given to the different aims were strongly influenced by the contribution of the aim to the composite. While the effectiveness and efficiency aims had higher numbers of eligible patients, the number of patients considered eligible for the safety and timeliness calculations tended to be significantly smaller.

Both multi-aim approaches required metrics in ratio form. The transformation of some of the QIs, such as TAS, TIL, and LOS, from a continuous metric to a ratio-type metric can be considered a limitation of the analysis. These transformations required the definition of a threshold. The choice of threshold impacted the resulting categorization of TCs. For example, if instead of the median, we had used a LOS threshold based on the findings of a study that addressed profitability (e.g., 11 days) [47] the resulting categorization would have been moderately different (2014: RI = 0.47).

Although the equity and patient-centeredness aims were as important as the other four aims according to the IOM, the practical assessment of both aims continues to remain a challenge, as

evidenced in the lack of published studies systematically measuring and analyzing them. The data did not have information related to the pre-hospital QIs identified from the literature to assess those aims. Nevertheless, this study proposed an approach to incorporate the equity aim into the analysis. While the specific equity QI used and the source of the disparity considered limit the generalizability of the results of this particular study, the underlying methodologies proposed can be adapted or expanded to include alternative or additional QIs once new sources of data become available.

The comparison in terms of a particular incentive program also concluded that both methods are different. The results showed that some TCs might prefer the E-WA O/E method and others the E-HQID method, because the preferred method would give them more incentives or fewer penalties at the end of the third year. Also, based on this three-year analysis, the payer might prefer the single-aim method for effectiveness because it would result in the payer owing no financial incentives to all TCs but instead having negative expenditures. For an incentive program different than the one used in this study, the preference for those stakeholders could change, as well.

The methodology and results of this study illustrated some of the challenges and opportunities related to the construction of a composite to assess the quality of trauma care considering the six aims of quality. The selection of QIs per aim and the methods of integrating them to represent each aim had an impact on TC categorizations. Only five aims were included in the analysis, which was a confirmation of what the literature has indicated: patient-centeredness is still a difficult aim to measure. The composite methods considered resulted in different trauma care assessments either when compared in terms of external benchmarking or in terms of a pay-for-performance program. In terms of benchmarking the E-WA O/E method could be selected by

TCs because of its similitude with current practices. In terms of an incentive program, the three-year analysis indicated that none of the methods was better for all TCs, but the E-HQID method presented a small economic advantage for the payer. The results of this study provided evidence of the effects of each method when evaluating trauma care quality from different perspectives. These insights are to support stakeholders in identifying which method could be the most appropriate to evaluate the quality of the TCs they want to improve.

2.5 Acknowledgments

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CHAPTER 3

MODELING AND ANALYSIS OF SHORT-TERM WORK PLANNING IN INPATIENT CARE SETTINGS

3.1 Introduction

Current inpatient care environments do not always allow nurses, and other inpatient care workers, to be as patient-centered as they intend [1]. Inpatient care workers are often expected to perform routine, simple tasks as well as knowledge-based, complex work during a single workday [2]. Furthermore, the introduction of state-of-the art quality improvement efforts often translate into extra tasks at the individual provider level. Inpatient care workers are then expected to incorporate the added work into their already busy workflows [3]. When the work is not appropriately designed, such efforts may result in stressed workers trying to meet multiple competing objectives throughout their workday, in turn leading to provider burnout over the long term [4]. Increasing patient acuity, the ensuing demand for quality and safety practices, and the importance of ensuring the well-being of healthcare workers underscore the need for efficient work planning strategies that support nurses and other inpatient care workers in efficiently spending their time on tasks for which they are trained [5].

Regardless of the model of care used by the organization [6–8], healthcare workers need to coordinate and execute a number of tasks. Oftentimes, healthcare workers do not have a clear understanding of how these processes should ideally work under different circumstances, which may result in "inefficiencies, higher operating costs, increased potential for errors and worker frustration" [8]. Traditional work design methods alone are insufficient to characterize inpatient care work. Task analyses using only human factors and work design tools often result in static descriptions such as process maps and analyses of the average time spent on different classes of

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tasks. Because of the high variability of patient care needs, work planning strategies that remain static over time may not always function as intended. Complex, variable work patterns suggest the need for more sophisticated analytical tools to study inpatient care work [3]. Nevertheless, work planning strategies should still incorporate relevant findings from human factors research [9].

Overall, the literature on OR in healthcare has steadily increased over the years [10, 11]. OR applications to healthcare typically focus on resource planning and utilization, quality management, performance monitoring, finance, policy and regulation, workforce management, and risk management in the medium- and long-terms [11–13]. While applications of OR to inpatient care services at the on-line operational level have mostly focused on elective admission rescheduling, acute admission handling, staff rescheduling, nurse-to-patient assignment, and patient transfer scheduling [14], the use of OR techniques to study short-term work planning decisions is limited. This research motivates the need for OR in the analysis of decisions made by a single provider over one workday when decisions at higher levels have been made; that is, resources have been allocated, and actual patients have been assigned. Although decisions at this level have been studied using OR techniques in manufacturing settings (e.g., the part-selection problem and the loading problem [15], they have not been studied in healthcare. The objectives of this study are as follows (1) to use OR as a platform to characterize short-term work planning decisions made by inpatient care workers, (2) to illustrate the potential of using OR in the analysis of such decisions, and (3) to generate research questions that motivate the use of OR in the design, analysis, and improvement of inpatient care work.

Section 2 provides a brief overview of the literature on inpatient care work analysis and proposes an inpatient care work classification framework to be used in model development. Section 3 introduces and illustrates a preliminary OR-based approach for the analysis of routine

work planning. Section 4 outlines opportunities for further research in modeling and analyzing inpatient care work. Section 5 presents concluding remarks.

3.2 Inpatient Care Work

We define inpatient care work as the set of tasks performed by a healthcare provider during a predetermined work period. Throughout this article, the term provider refers to healthcare workers whose job involves several interactions with a specific set of patients throughout a single workday.

3.2.1 Inpatient Care Work Analysis Research

To gain insight into inpatient care work research, we reviewed a sample of the literature that studied the work of inpatient care providers, including nurse assistants, nurses, and hospitalists. The majority of studies focused on nursing, but some focused on nurse aides, hospitalists, and residents. We included peer-reviewed articles focusing on inpatient care work during a single workday, which may consist of a day or a night shift.

Most inpatient care work research originates from the healthcare research community. Traditional work design methods are commonly used for data collection and analysis, including time and motion studies [16], task analysis [17], work sampling [18], and ‘‘human factors engineering methods’’ [19]. The most common analysis approach is to classify observed tasks into categories. Most consistently, studies evaluate if observed tasks correspond to direct or indirect care and general strategies to reduce time spent on indirect care are often discussed [20]. Studies using OR techniques to analyze or improve inpatient care work planning and execution decisions were not found.

A portion of this literature highlights the importance of interruptions during inpatient care work. Interruptions are commonly seen as disruptions to workflow and thus as events to be

eliminated [21]. Nevertheless, the negative impact of interruptions on healthcare outcomes is debated [22] because many of these unpredictable events can be integral to the delivery of care. Kowinsky et al. [23] classify inpatient care tasks as predictable vs. unpredictable based on their expected frequency during a single shift. They underscore the need to design roles that ensure the consistent and timely completion of both types of tasks.

While comments related to workload can be found throughout the literature in terms of time spent in tasks, distance traveled to provide care in a shift [24], inadequate posture [25], cognitive load [26], and high-effort work patterns [27], such considerations are often overlooked by providers in practice. Currently, there is much research describing workload but no formal workload metrics to proactively support the delivery of inpatient care [28].

Operational goals for inpatient care delivery include delivering the right care at the right time [23], minimizing workload [29], minimizing task switching [3] and reducing negative consequences of interruptions [30]. These goals are consistent with the timeliness, efficiency, safety, and effectiveness aims for healthcare quality defined by the Institute of Medicine (IOM).

Overall, the inpatient care work analysis literature tends to be retrospective and descriptive. There is a need to use the knowledge obtained from these studies to support the design of inpatient care work systems. In what follows, we propose a classification of inpatient care tasks based on the literature findings above as well as observation of patient care assistants (PCAs) in an inpatient care unit. This classification is used as the basis of the proposed framework for inpatient work planning research.

3.2.2 Inpatient Care Task Classification for Short-Term Work Planning

To support the analysis of short-term work planning decisions, we focus on the time requirements of common inpatient care tasks. We expand the task classification proposed by

Kowinsky et al. [23], as shown in Figure 4.1. Unpredictable tasks are those that arise randomly throughout the workday, while predictable tasks are known from the beginning of the workday. Unpredictable tasks may occur anytime or within a time window. Predictable tasks can have a specified target time (i.e., fixed time) or can have a specified frequency but no target time. Note that this classification uses the term ‘‘predictable’’ in reference to the expected incidence of tasks throughout the workday. Task durations are random, regardless of task type.

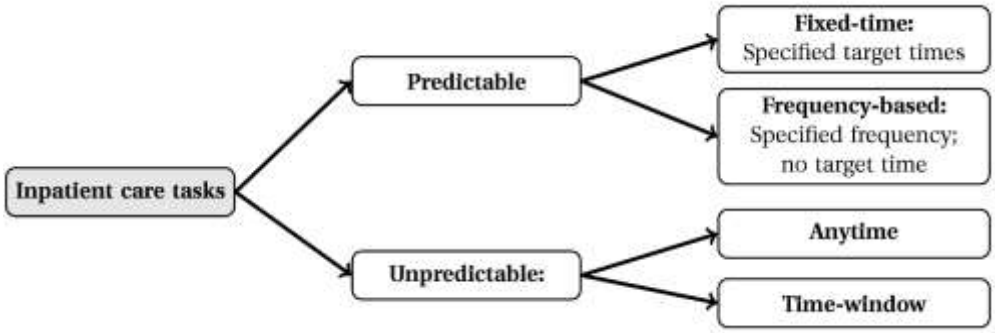

Figure 3.1. Proposed classification of inpatient care tasks (based on [23]).

We further classify tasks according to their demand as patient-independent and patient-dependent. Patient-independent tasks are those associated with all patients in the ward, regardless of their condition, whereas patient-dependent tasks correspond to patients with specific characteristics, namely patient factors [31]. This classification helps in establishing the task list once the factors of the assigned patients are known. Examples of patient factors include the following: need for incision care (or not), level of independence (e.g., on bedrest vs. independent patient), blood sugar level checks required (or not), among others, depending on the unit and on the provider type. In the collaborating unit, the patient factors and associated tasks were found in the PCAs’ ‘‘expectation sheet,’’ where target times and frequencies of tasks are also specified. The PCA identified those factors associated with the assigned patients from the handoff meeting and from the electronic medical records. With this information they created a mental plan, often supported

by a paper ‘‘cheatsheet,’’ of the predictable portion of their workday (Figure 4.2). In general, although much of professional inpatient care work is knowledge-based and inpatient care workers are expected to constantly assess, prioritize and make decisions (unpredictable work), they are also assigned a number of routine, predictable tasks, depending on their professional level. Having a temporal plan of work is common among providers such as nurses because it brings a sense of order [32]. Work organization strategies include batching [20] and assigning blocks of time for similar activities [33], which are consistent with observed strategies. The next section focuses on the analysis of the predictable portion of inpatient care work.

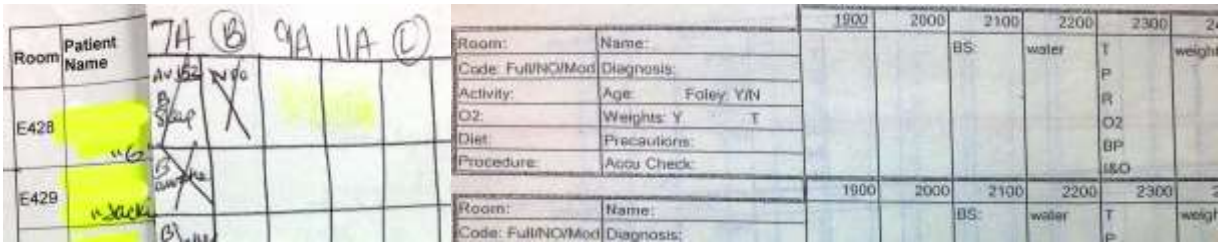

Figure 3.2. Examples of ‘‘cheat-sheets’’ used by observed providers to manually organize their workday into hourly rounds.

3.3 Work Planning: Predictable Task Allocation to Rounds

Healthcare providers organize their work in terms of rounds formed by a subset of tasks to perform consecutively over a set of patients for a specific period of time. Organizing work in rounds facilitates the use of memory by keeping a relatively small subset of tasks in the short-term mental queue, thus reducing cognitive load. Rounds, defined as predefined time periods for specific tasks, reduce the time needed to think about time management during the workday [32] and support staff satisfaction and patient safety [34].

Observed PCAs were asked about strategies they used to plan for predictable tasks at the beginning of their shift. Although specific strategies varied for different PCAs, all had the common goal of performing fixed-time tasks as close as possible to their target time. Frequency-based tasks,

however, were mainly accommodated as the workday progressed when other tasks allowed. A few of the PCAs assigned a specific target time to frequency-based tasks, based on their experience. None of the other goals identified in the literature were explicitly mentioned by the PCAs as being considered in planning for their workday. However, it was observed that the physical location of patients had an influence on how tasks were sequenced per round. Unpredictable tasks were also not explicitly considered in the work plan. Rounds were initially determined by the target times of fixed-time tasks, and unpredictable tasks were accommodated as they presented themselves, mainly as calls from patients and other staff. We noted that the (expected) durations of tasks were not found in any documents available to the researchers; rather, task durations were informally assessed by PCAs according to their experience. Variability in these durations was also not explicitly considered, although it was always expected.

Figure 4.3 exemplifies time requirements for predictable work associated with four different mixes of seven patients based on the observed average task durations. The work planning decision can be defined in OR terms as an assignment problem where predictable tasks are assigned to the rounds where they best fit [35–38]. PCAs often use fixed strategies to assign these tasks to rounds (see Figure 4.2). Nevertheless, Figure 4.3 illustrates that a fixed strategy, even for the same number of patients and assuming no variability in task durations, may not be effective for different patient mixes. In what follows, we use the assignment problem as a framework to describe and study the inpatient care workday planning problem. The task-sequencing problem, i.e., deciding which task to perform next, is not included in the model. Given a recommended workday plan, healthcare workers can have the flexibility of sequencing the tasks within rounds as they consider appropriate, taking into consideration information about actual task durations and unpredictable task incidence. This model is used to demonstrate interesting implications of work

planning decisions as well as to identify opportunities to formally study inpatient care work and develop systematic work planning strategies that better fit inpatient care work dynamics.

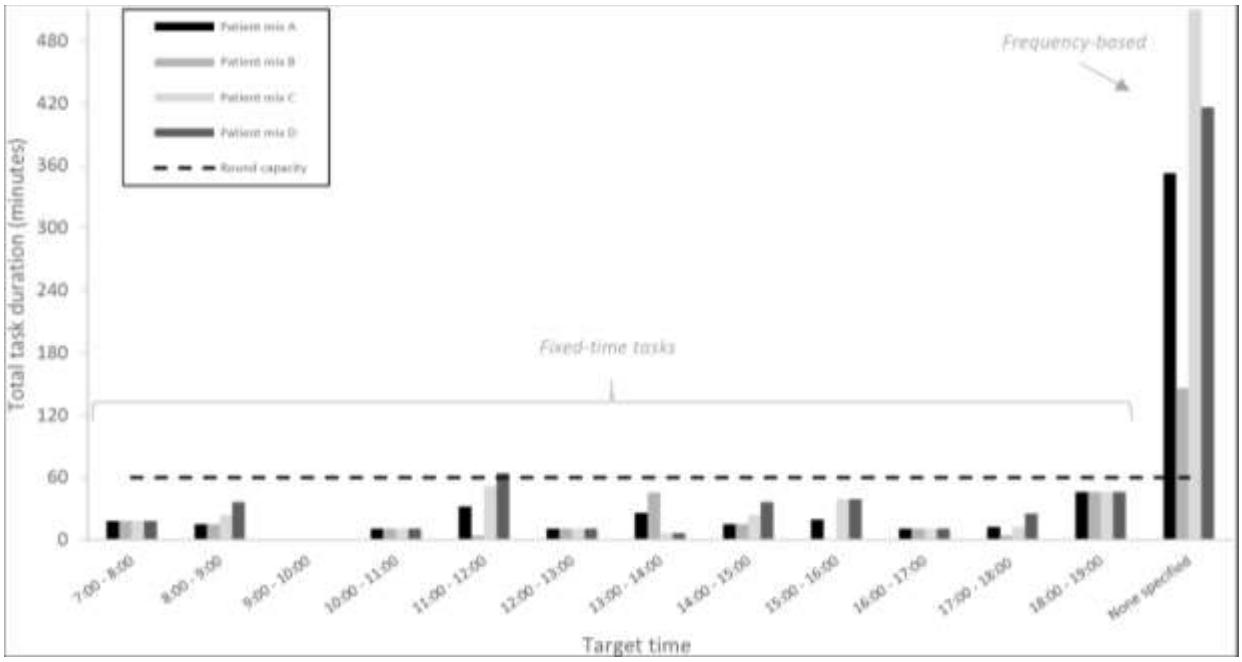

Figure 3.3. Expected predictable work distribution according to target times for different assignments of seven patients. For example, Patient mix A has seven patients, out of which three require vitals every four hours, three have NPO orders, one has AC/HS blood glucose check (ACHS) orders, and two require bedrest. On the other hand, Patient mix D has seven patients out of which six require vitals every four hours, six have NPO orders, six have ACHS orders, six require bedrest, and all require incision care.

3.3.1 Problem Formulation

We assume an assignment of patients to a single provider at the beginning of the workday with their corresponding set of predictable tasks, consistent with the ‘‘Primary Nursing’’ model of care [6]. The workday consists of a 12-h shift. A predetermined rounds structure, which specifies the timing, duration, and available time for each round, is also assumed. The goal here is to optimally allocate predictable tasks to rounds. The optimization criteria consist of one or more operational performance metrics representing healthcare delivery quality and that can be influenced by the selected task assignment. The proposed formulation is a special case of the 0–1

generalized assignment problem with nonlinear capacity interactions (NLGAP) [36]. In this formulation, potential nonlinear interactions are limited to disjoint pairs of tasks indexed by h in set $\mathscr{S}$. The vector of decision variables, denoted by $\boldsymbol{x} = (x_{it} : i \in \mathscr{I}, t \in \mathscr{T})$, represents the tasks assignment to rounds; that is, $x_{it} \in \{0, 1\}$ indicates whether task $i \in \mathscr{I}$ is assigned to round $t \in \mathscr{T}$. In addition, we use a vector of auxiliary decision variables, denoted by $\boldsymbol{y} = (y_{ht} \in \{0, 1\} : h \in \mathscr{S}, t \in \mathscr{T})$, to indicate if a set of two tasks, denoted by $\mathscr{Q}_h$, should be done simultaneously in round t ($y_{ht} = 1$) or not ($y_{ht} = 0$). The rounds scheduling problem is formulated as follows:

Notation Summary

$\mathscr{K}$	set of all patients, indexed by k
$\mathscr{T}$	set of rounds in a shift, indexed by t
$\mathscr{I}$	set of tasks, indexed by i
$\mathscr{N}$	finite set of evaluation criteria, indexed by n
$\mathscr{J}$	index set of pairs of consecutive frequency-based tasks of the same type
$\mathscr{R}_j$	jth pair of consecutive frequency-based tasks of the same type ($\mathscr{R}_j \subseteq \mathscr{I}, j \in \mathscr{J}$)
$\mathscr{S}$	index set of subsets of tasks that can be done simultaneously, if any (i.e., "potentially simultaneous")
$\mathscr{Q}_h$	hth subset of potentially simultaneous tasks ($\mathscr{Q}_h \subseteq \mathscr{I}, h \in \mathscr{S}$)
σ_h	time savings from assigning potentially simultaneous tasks in $\mathscr{Q}_h$ to round t
p_i	(mean) duration of task i
r_i	release time of task i
d_i	due time of task i
β_j	desired time between tasks in $\mathscr{R}_j$
F_n	nth optimization criterion, when more than one performance metric is used

s_t start time of round t

a_t end time of round t

e_t available time within each round t ($e_t < a_t - s_t$ due to allowance)

Model (P)

$$Minimize\ \left(F_1(x), F_2(x), \dots, F_n(x)\right)$$

s.t.:

$$\sum_{t \in \mathscr{T}} x_{it} = 1 \quad \forall\, i \in \mathscr{I} \tag{1}$$

$$\sum_{t \in \mathscr{T}} p_i\, x_{it} - \sum_{h \in \mathscr{S}} \sigma_h\, y_{ht} \le e_t \quad \forall\, t \in \mathscr{T} \tag{2}$$

$$y_{ht} \le \begin{cases} 1, \text{ if } x_{i_1 t} = 1,\ x_{i_2 t} = 1 \\ 0, \text{ otherwise} \end{cases}$$

$$t \in \mathscr{T},\ h \in \mathscr{S} \text{ with } \mathscr{Q}_h = \{i_1, i_2\} \text{ and } i_1, i_2 \in \mathscr{I} \tag{3}$$

$$\sum_{i \in \mathscr{I}} \sum_{h: i \in \mathscr{Q}_h} y_{ht} \le 1 \quad \forall\, i \in \mathscr{I} \tag{4}$$

$$\sum_{t \in \mathscr{T}} s_t\, x_{i_2 t} - \sum_{t \in \mathscr{T}} a_t\, x_{i_1 t} \ge \beta_j$$

$$\forall\, i \in \mathscr{I} \text{ with } \mathscr{R}_j = \{i_1, i_2\} \text{ and } i_1, i_2 \in \mathscr{I} \tag{5}$$

$$x_{it} \in \{0, 1\} \ \forall\, i \in \mathscr{I}, t \in \mathscr{T} \tag{6}$$

$$y_{ht} \in \{0, 1\} \ \forall\, h \in \mathscr{S}, t \in \mathscr{T} \tag{7}$$

Each activity should be assigned to one round, assuming that a task may not be broken into two different rounds (constraint set (1)).

Activities assigned to a single round need to be carried out within the effective assignable time of the round (constraint set (2)). In its strictest form, the task durations in this problem are not deterministic but random. One way to incorporate task duration variability in a work plan is to use the expected values for task durations in the deterministic version of the model and to include an allowance or slack per round representing the expected impact of variability on workload [39–41]. This allowance is also used for buffering unpredictable work arising during the round [39]. Thus, the right-hand side of constraint set (2), is less than the actual round duration. Furthermore, some tasks may be performed simultaneously. For example, in the unit of study, a fall-risk check can be done while measuring the vital signs of a given patient, because a fall-risk check only encompasses a visual check of the patient environment. Considering only pairs of potentially simultaneous activities, let $\mathscr{S} \subseteq \{\mathscr{Q} \subseteq \mathscr{I} : |\mathscr{Q}| = 2\}$ be the set of pairs of tasks that can be performed simultaneously (sets in $\mathscr{S}$ are indexed by h). Let $\sigma_h > 0$ represent the time saved when performing tasks in the hth set ($i \in \mathscr{Q}_h$) in the same round t, so that $\sigma_h = \min_{i \in \mathscr{Q}_h} \{p_i\}$. This assumes that for tasks that can be performed simultaneously, only the longer task will consume round time capacity. A formal study needs to be performed to identify sets of tasks that can or cannot be done simultaneously and the corresponding time savings [29]. An expression incorporating simultaneous tasks in a round is shown in the second term of the left-hand side of constraint set

(2). This expression can also be used to incorporate the effect of activities with an increased setup cost when done in the same round, such as walking outside the room to pick up additional supplies.

Constraint set (3) connects $\boldsymbol{x}$ and $\boldsymbol{y}$ logically and allows the bundling of two potentially simultaneous tasks only if they are assigned to the same round. In solving the problem, this constraint set was replaced with the following linear constraint set, which ensures that the savings associated with a pair of potentially simultaneous tasks is realized only if both tasks are assigned to the same round:

$$x_{i_1 t} + x_{i_2 t} - 2y_{ht} \geq 0$$

$$\forall\ i_1, i_2 \in \mathscr{I}\ ,\ \mathscr{Q}_h = \{i_1, i_2\},\ \mathrm{h} \in \mathscr{S},\ t \in \mathscr{T} \qquad (8)$$

Constraint set (4) ensures that each task i $\in \mathscr{I}$ is bundled with, at most, one other task.

Consecutive frequency-based tasks of the same category may need a minimum time between occurrences (constraint set (5)). $\mathscr{J}$ represents the set of pairs of frequency-based tasks of the same type that require a minimum time between them ($\mathscr{J}$ = {1, . . . , |{$\mathscr{R} \subseteq \mathscr{I}$, |$\mathscr{R}$|= 2}|}) and β_j, the required minimum time between tasks in the pair $j \in \mathscr{J}$.

The resulting model has |$\mathscr{I}$ ‖ $\mathscr{T}$ | + | $\mathscr{S}$ ‖ $\mathscr{T}$ | variables and up to 2|$\mathscr{I}$ | + | $\mathscr{T}$ | + | $\mathscr{S}$ ‖ $\mathscr{T}$ | + | $\mathscr{J}$ | constraints.

3.3.2 Objective Function

The objective function is to minimize a finite collection of evaluation criteria. Without loss of generality, it is assumed that smaller values of the evaluation criteria are preferred to larger ones. Evaluation criteria that explicitly represent healthcare quality are investigated. According to the IOM, healthcare quality improvement efforts should be aimed at enhancing: safety, timeliness, effectiveness, efficiency, equitability, and patient-centeredness [42]. Because it is expected that actual patient factors are used to forecast predictable tasks for the shift, the proposed approach indirectly supports *patient-centeredness*. Furthermore, these patient factors are determined by medical requirements, rather than personal characteristics such as ethnicity or socioeconomic status; thus, the proposed approach indirectly supports *equitability*. The medical indication of services to patients is out of the scope of this research; thus, *effectiveness* is not directly addressed by this model. In what follows, preliminary metrics corresponding to *timeliness*, *patient safety*, and *efficiency* are proposed.

3.3.2.1. Timeliness

- Minimizing tardiness cost

  In practice, healthcare workers are given an ideal (target) time to perform each type of task (e.g., vital signs documented at 9:00 a.m.) for all patients, with a desired time window (e.g. within one hour of the target time). Thus, providers do their best to perform each activity as close as possible to this target time, as other activities allow and depending on their (implicit) priority. Therefore, this objective can be modeled as the minimization of a cost that rewards timeliness and penalizes lateness or earliness. The cost of assigning a task to a specific round should then be a function of the task time requirements and the time of the round. For example, the aim could be to minimize the maximum difference between the task's due time and the round's end time. Using the expected time windows, release and

due times (r_i and d_i, $i \in \mathscr{I}$, respectively) can be estimated for each task, and a corresponding cost coefficient can be determined. This cost parameter per task–round combination (ζ_{it}) can incorporate a significant penalty for assigning tasks to rounds that start earlier than the task's release time:

$$\zeta_{ht} \leq \begin{cases} 1, \text{if } r_i < s_t, a_t \leq d_i \\ |d_i - a_t|, \text{otherwise} \end{cases} \quad \forall\, i \in \mathscr{I}\ , \forall\, t \in \mathscr{T}$$

Total tardiness is then defined as

$$F_1(x) = \sum_{i \in \mathscr{I}} \sum_{t \in \mathscr{T}} \zeta_{it}\, x_{it} \tag{9}$$

For frequency-based tasks, timeliness may not be a direct objective, since in theory there is no due time for such tasks. The decision then is to allocate frequency-based activities to the most appropriate round to ensure the timeliness of fixed-time tasks under a feasible, balanced schedule, i.e., tasks are evenly distributed throughout the shift. Nevertheless, because it is likely that the variability of task durations and unpredictable tasks may cause delays in the performance of some tasks, it may be preferable to schedule frequency-based tasks as early as possible so that any delays can be accommodated in later, looser and more flexible rounds. The makespan can be used to represent this objective.

- Minimizing makespan (for frequency-based tasks) Makespan is defined as the time required to complete all (frequency-based) tasks. Minimizing makespan ensures that tasks are scheduled as early as possible and reduces the number of tasks at the end of the shift. For this proof of concept, and to mimic common strategies used by the observed PCAs, we use tardiness as a surrogate for makespan. Thus, for frequency-based tasks, release time is

set to 0, if there are no constraints on how early these tasks should be performed, and due time is set to early rounds.

3.3.2.2. Safety

Recommended practices to reduce patient falls [43], central line-associated blood stream infections [44], catheter-associated urinary tract infections [45, 46], and pressure ulcers [47, 48] involve frequent visits to patients to prevent high-risk situations from evolving into adverse events. Thus, in addition to ensuring the timely execution of such visits, maximizing patient-provider contact can support many patient safety efforts. This motivates use of the following safety-related goals:

- Maximizing the minimum number of rounds in which each patient is visited, which can be expressed as

$$F_2(x) = -\min_{k \in \mathscr{K}} \left\{ \sum_{t \in \mathscr{T}} I_{kt}(x) \right\} \tag{10}$$

  where binary indicator $I_{kt}(x)$ shows if patient k is visited at least once in round t. This criterion does not guarantee that the visits to a single patient span across the entire shift. To circumvent this issue, the following alternative goal may be used:

- Maximizing the minimum time between the first and last rounds over all patients, which can be written as

$$F_3(x) = -\min_{k \in \mathscr{K}} \{ \max_{t \in \mathscr{T}} \{ a_t : I_{kt}(x) = 1 \} - \min_{t \in \mathscr{T}} \{ a_t : I_{kt}(x) = 1 \} \} \tag{11}$$

3.3.2.3. Efficiency (workload)

Rather than material resources, the work planning decision involves people. The efficiency dimension of care quality needs then to actively incorporate provisions to minimize or balance the workload of providers. The following objectives can be used to incorporate workload into the work planning decision:

- Minimizing the spatial dispersion of tasks per round, which can be defined as the sum of the square distances of tasks in round $t \in \mathscr{T}$ to their centroid (f_t) and estimated as

$$f_t = \frac{\sum_{i \in \mathcal{I}} \emptyset_i x_{it}}{\sum_{i \in \mathcal{I}} x_{it}} \quad \forall\, t \in \mathscr{T} \tag{11}$$

  where ϕ_i is the physical location of task $i \in \mathscr{I}$. Although this metric is not explicitly meaningful on its own, the spatial dispersion metric can provide an idea of the extent of the physical area that would need to be covered by the worker within a round, and thus, it is useful in comparing work plans. The objective then would be to minimize the sum of the squared distances, or scatter [49], as follows:

$$F_4(x) = \sum_{t \in \mathscr{T}} \sum_{i \in \mathscr{I}} dist\,(\emptyset_i, f_t)^2\, x_{it} \tag{13}$$

  The preferred distance metric, *dist*, can be used.

- Minimizing cognitive shifts, which are defined as a change in the provider's focus of attention from one patient to another, contributing to increased cognitive load on the provider [26]. To minimize the cognitive shifts, it is ideal to minimize the number of distinct patients seen in a single round. This research uses the average number of distinct patients seen per round (to be minimized), defined as

$$F_5(x) = \frac{\sum_{t \in \mathscr{T}} \sum_{k \in \mathscr{K}} I_{kt}(x)}{|\mathcal{T}|} \tag{14}$$

- Minimizing the maximum utilization of rounds helps balance the workload of providers throughout their workday and avoid periods with excessive work demands. The utilization of a round is defined as the busy proportion of round time and can be formulated as

$$F_6(x) = \max_{t \in \mathscr{T}} \left\{ \frac{G_t(x)}{e_t} \right\} \tag{15}$$

where $G_t(x)$ is the total time of tasks assigned to round $t \in \mathscr{T}$, which is equivalent to the left-hand side of constraint set (2).

The objectives above are just a sample of the possible ways in which the quality of a work plan can be evaluated. Depending on the application or the actual setting of analysis, even the use of the IOM quality aims may be expanded or replaced by other healthcare quality improvement frameworks. While some of the proposed evaluation criteria are synergistic, others are conflicting, making it difficult for providers to consistently consider them all as they plan for their workday. For instance, in objectives (10) and (11), the ideal situation is to see all patients in most rounds. On the other hand, objectives like (13) and (14) will cause the model to assign tasks associated with as few patients as possible to each round. Thus, there is a need to identify synergistic objectives and quantify the trade-offs between conflicting ones to support decision-making.

In the proposed formulation, constraint set (5) and the different forms of criteria involved in the objective function make the problem a variation of the NLGAP, which has been shown to be NP-complete [36]. The spatial dispersion, $F_4(x)$ function requires the use of clustering, in addition to optimization, techniques. The *k*-means algorithm can be used to find the task assignment with minimum spatial dispersion. A general constrained *k*-means algorithm for the

proposed problem is shown in Table 1. The complexity of the constrained k-means approach will depend on the solution approach to (P).

TABLE 3.1.

CONSTRAINED k-means APPROACH FOR TASK ASSIGNMENT TO ROUNDS WHERE $k = |\mathscr{T}|$ (BASED ON [49]).

1. Set $iter = 0$ and initialize $\boldsymbol{f}^{(0)}$	May use optimal-timeliness solution to (P)
repeat	
2. $\boldsymbol{x}^{(iter+1)} = \text{argmin}_{\boldsymbol{x}} \left\{F_4(\boldsymbol{x}; \boldsymbol{\phi}, \boldsymbol{f}^{(iter)}) : (1)\text{–}(6)\right\}$	
3. Compute $\boldsymbol{f}^{(iter+1)}$ using $\boldsymbol{x}^{(iter+1)}$	Using Eq. (12)
2. $iter \leftarrow iter + 1$	
until $\boldsymbol{f}^{(iter)} - \boldsymbol{f}^{(iter-1)} \leq \epsilon$	Where ϵ is a small positive number

3.3.3 Case Study

In the collaborating unit, PCAs are usually assigned between seven to ten patients with varying needs. To analyze the implications of the proposed modeling approach, we performed a pilot observational study to identify tasks, map the identified tasks to observable patient factors, estimate task durations, and implement the model. Study resources allowed for a total of 51.5 observation hours and resulted in sample sizes ranging from 1 to 18 observations for most tasks. Interviews with PCAs and unit managers were conducted to define durations for tasks not observed. Using the preliminary task-to-patient mapping identified, we generated random instances with patient assignments ranging from 7 to 10 patients having varying factors and simulated their associated task demands for the shift. One of the feasible instances (Patient Mix A) is used to illustrate the analysis in detail. Summary results for these instances are given in Table 2. Patient Mix A consists of seven patients, of which three require vitals every four hours, three have NPO orders, one has ACHS orders, and two require bedrest. These patients and their factors result in a total of 168 predictable tasks (137 fixed-time and 31 frequency-based tasks). These task requirements were illustrated previously in Figure 4.3 in Section 3. Using the available data and

Monte Carlo simulation techniques, a 10-min fixed allowance per round was estimated for a 50% probability of being able to address unpredictable work in the round and assuming that the total time of unpredictable tasks in each round is Normally distributed per the Central Limit Theorem [39]. Therefore, for each 60-min round t, an available time e_t of 50 min was used. A minimum time between frequency-based tasks of the same type of β = 2 h was used.

TABLE 3.2.

PERFORMANCE METRIC VALUES FOR OPTIMAL-TIMELINESS AND OPTIMAL-SPATIAL DISPERSION SOLUTIONS OF VARIOUS PATIENT MIX INSTANCES.

				Optimal-timeliness solutions (x_1)								*Optimal-spatialdispersion solutions (x_2)*						
Instance	No. of patients	Variables	Constraints	Run time (s)	Output/Gap	F_1^* (min)	F_2 (rounds)	F_3 (h)	F_4 (m^2)	F_5 (patients)	F_6	k-means iterations	F_1 (min)	F_2 (rounds)	F_3 (h)	F_4^* (m^2)	F_5 (patients)	F_6
A	7	11,952	10,336	1.37	0	3690	−8	−11	6,730	5.5	1.00	4	31,770	−2	−3	427	2.0	0.99
B	7	8,256	6,952	0.89	0	3030	−9	−11	5,467	5.7	1.00	4	29,310	−2	−4	470	1.7	1.00
C	7	14,028	12,372	7.82	0	4110	−9	−11	6,770	6.0	0.99	4	35,130	−2	−1	97	2.0	0.99
D	7	13,968	12,111	–	infsbl.	–	–	–	–	–	–	–	–	–	–	–	–	–
E	8	9,336	7,859	1.15	0	3510	−8	−11	7,569	5.9	0.99	5	33,570	−2	−1	651	2.2	1.00
F	8	11,496	9,652	–	infsbl.	–	–	–	–	–	–	–	–	–	–	–	–	–
G	8	12,300	10,638	–	infsbl.	–	–	–	–	–	–	–	–	–	–	–	–	–
H	8	11,208	9,613	–	infsbl.	–	–	–	–	–	–	–	–	–	–	–	–	–
I	8	14,484	12,694	4.57	0	4590	−8	−11	8,790	5.8	0.99	5	41,190	−2	−1	444	1.7	1.00
J	8	16,176	14,047	–	infsbl.	–	–	–	–	–	–	–	–	–	–	–	–	–
K	8	17,580	15,366	–	infsbl.	–	–	–	–	–	–	–	–	–	–	–	–	–
L	9	12,600	10,816	2.39	0	4230	−8	−11	11,337	7.2	1.00	5	39,450	−2	−1	775	2.3	1.00
M	9	12,456	10,418	–	infsbl.	–	–	–	–	–	–	–	–	–	–	–	–	–
N	9	12,912	11,106	–	infsbl.	–	–	–	–	–	–	–	–	–	–	–	–	–
O	9	16,968	14,918	26.12	0	5070	−9	−11	12,634	7.7	1.00	4	49,170	−3	−2	311	2.4	0.98
P	10	13,680	11,723	49.28	0	4830	−7	−11	15,731	7.3	1.00	4	41,310	−3	−2	489	3.1	1.00
Q	10	13,572	11,329	–	infsbl.	–	–	–	–	–	–	–	–	–	–	–	–	–
R	10	13,368	11,425	–	infsbl.	–	–	–	–	–	–	–	–	–	–	–	–	–
S	10	13,680	11,719	–	infsbl.	–	–	–	–	–	–	–	–	–	–	–	–	–
T	10	18,048	15,827	77.64	0	5730	−9	−11	18,076	9.2	1.00	6	50,850	−2	−1	1047	2.6	1.00

To begin the analysis using the most widely used objective among the observed providers, IBM CPLEX Optimization Studio (version 12.6.3) was used to solve the problem with the tardiness objective function. Figure 4.4 shows the duration distribution of the optimal tardiness schedule for Patient Mix A. This figure helps to visualize how balanced the work plan could ideally be throughout the shift as well as the available time for unpredictable work and variability in task duration. Table 3 illustrates the information that could be available to the provider.

The optimal tardiness was $F_1*(\boldsymbol{x_1})$ = 3, 690 min. Table 4 summarizes the distribution of the lateness and earliness of fixed-time tasks. When the expected tardiness is less than or equal to 30 min, the task could still be done on time, depending on how early or late within the round it is actually performed. The minimum number of rounds in which a patient was visited was $-F_2(\boldsymbol{x_1})$ = 8 rounds, and the minimum time between the first and last visits was $-F_3(\boldsymbol{x_1})$ = 11 h, thus showing that visits to patients were frequent and that all patients were seen at least once at the beginning and end of the shift. Therefore, patient safety metrics are at a satisfactory level. The optimal tardiness assignment had a spatial dispersion of $F_4(\boldsymbol{x_1})$ = 6729.7 m2. On average, $F_5(\boldsymbol{x}_1)$ = 5.5 different patients were seen per round. The maximum utilization over all rounds was $F_6(\boldsymbol{x}_1)$ = 1.00 (100% of effective assignable time scheduled).

In principle, the output from a modeling approach like the one proposed in this paper could be used to replace generic, fixed job descriptions, as well as manual and fixed work plans such as the ones illustrated in Figure 4.2, with shift-dependent work plans such as the one shown in Table 3. Even if timeliness was the only objective to consider, as often occurs in practice, a shift-dependent work plan can help reduce the need for providers to spend time and mental effort in planning for frequency-based tasks while ensuring consistency in the allocation of tasks to rounds, at least initially. This information could be incorporated into a portable electronic device linked to the patient's electronic medical records to guide the execution of tasks. In addition, the proposed set of constraints can be useful in identifying situations when the assignment is not reasonable at some level even in ideal (deterministic) circumstances, i.e., when a feasible solution is not found. Table 2 shows that many of the instances generated had no feasible solution. The main reason was the total time of the tasks associated with the patient assignment and allowances used; not necessarily the number of patients, their characteristics or the number of tasks. A mathematically

infeasible instance can then indicate a patient assignment for which the provider will have difficulty in consistently meeting the standard requirements under a reasonable workload. The consequences of an instance with no feasible solution, assuming task duration and allowance estimates are accurate, may then include the worker experiencing lack of time, asking for help in performing some tasks, leaving tasks undone, or engaging in workarounds that may compromise safety [50, 51].

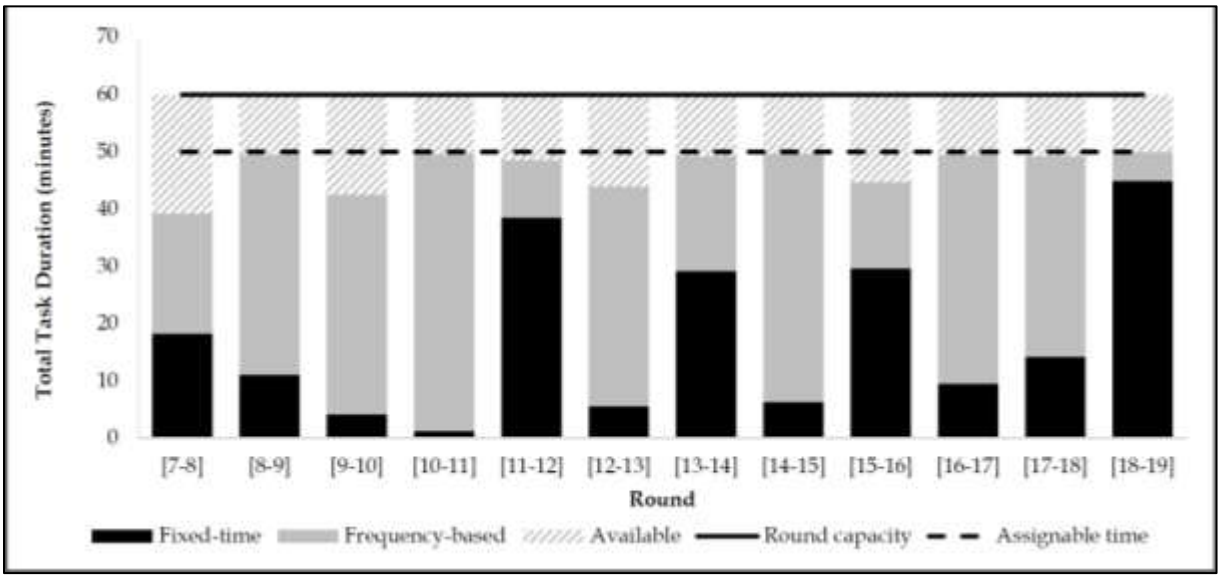

Figure 3.4. Optimal-timeliness predictable work distribution (patient mix A).

The optimization model can help specify strategies to support healthcare workers in performing assignments without mathematically feasible work plans. Table 5 specifies three example strategies for each one of the infeasible scenarios identified. The first strategy considered was to delegate unpredictable work to other (presumably available) workers, which translates into reducing round allowances in the formulation. This table shows that only a couple of scenarios (G and H) would potentially benefit from such strategy alone, i.e., the time saved in allowances is not sufficient to cover for the total task durations associated with the assignment in most of the scenarios studied. Therefore, alternative strategies are needed. The other option is to delegate part

of the predictable tasks to another worker, if available. Tasks can be ranked in decreasing order of expected duration to identify a relatively small number of tasks to be delegated. In the optimization model, such tasks can be removed iteratively from the predictable task list until a feasible solution is found. In the case study, the bathing task takes comparatively longer than other tasks. Thus, having someone else perform some of the assigned baths would significantly help the worker. Another option when no additional workers are available involves overtime work. The model can then be used to identify the number of overtime rounds needed to perform all tasks. Table 5 shows that the number of additional rounds alone needed to achieve feasibility could range between 2 and 7. The most appropriate strategy (or combination) would be determined taking into consideration the availability of resources and associated costs.

Before attempting to incorporate all the objective functions in a solution, we proceeded to study the relationship between the proposed objectives. We first compared timeliness ($F1$) with spatial dispersion (F 4) using the ϵ-constraint method [52]. We initially picked these two objectives because they are the most intuitive among the proposed metrics and because we suspected that they may be conflicting. We minimized spatial dispersion using different tardiness values as an additional constraint. For each efficient solution associated with these two objectives, the values of the remaining metrics were also calculated and compared to each other. The matrix plot shown in Figure 4.5 helps visualize these solutions for three instances of different patient sizes. The relationships between the objective functions had similar behaviors for all other instances with feasible solutions (not included in the plot to avoid clutter). The plot at the intersection of F_1 and F4 represents the efficient solutions when considering only these two objectives and confirms that the two are conflicting. For this particular set of task parameters, we find that tardiness (F 1) is positively correlated with safety objectives (F_2 and F_3), while spatial dispersion (F_4) conflicts with

most other objective functions, except for number of patients seen per round (F_5). Maximum utilization of rounds (F_6) does not seem to have a significant relationship with the other metrics. This is mainly because the model constrains the available time per round, which helps balance the schedule when the total durations are tight.

In the example, the inpatient care work planning decision can be reduced to minimizing tardiness while minimizing the spatial dispersion of tasks, which are conflicting. When solving for optimal spatial dispersion, the tardiness increased eightfold to $F_1(\boldsymbol{x_2})$ = 35, 770 min while the spatial dispersion was reduced to $F_4{*}(\boldsymbol{x_2})$ = 427.45 m2, and the other objectives follow the approximate patterns illustrated in Figure 4.5. The proposed modeling approach can help visualize the trade-offs between these two metrics and select a work plan that balances both objectives, in order to avoid work plans that are suboptimal in both dimensions. This information could help providers and decision-makers understand the effects of their work planning expectations and decisions on the different dimensions of healthcare delivery quality at the operational level. The relationships shown in Figure 4.5 may depend on the characteristics of the unit, i.e., the physical layout, model of care used, and task requirements. Therefore, each inpatient care unit should perform a similar analysis to identify its own key operational performance metrics for high-quality work planning. In general, it may be reasonable to expect a conflict between timeliness and spatial dispersion in most inpatient care settings where providers are assigned multiple patients with different physical locations and when the task requirements are defined per task type. On the other hand, a provider for whom target times are specified per patient (e.g., patient 1 must be seen by 9:00 a.m., patient 2 must be seen by 10:00 a.m., and so on) will likely find a positive correlation between timeliness and spatial dispersion, given that the target times are consistent with patient locations. Although this type of schedule is uncommon in inpatient care nursing, it could be the

case for more specialized providers of ancillary services to inpatient care units such as radiologists and social workers, whereby additional performance metrics may be of interest.

TABLE 3.3.

SAMPLE TASK SCHEDULE (FIRST THREE ROUNDS OF OPTIMAL-TARDINESS SCHEDULE SORTED BY ROUND AND BY PATIENT; NO SEQUENCE OF TASKS IS SUGGESTED).

Round	Patient	Task
7:00–8:00 **20.7** min available	1	Passing water Update board
	2	Passing water Update board
	3	Passing water Update board
	4	Passing water Update board
	5	Passing water Update board
	6	Passing water Update board
	7	Passing water Update board
	–	Shift huddles PCA updates RN updates
8:00–9:00 **10.6** min available	1	Fall-risk check 1 (includes turning) Fall-risk check 1 doc
	2	Fall-risk check 1 (includes turning) Fall-risk check 1 doc Bathing
	3	Fall-risk check 1 (includes turning) Fall-risk check 1 doc
	4	Fall-risk check 1 (includes turning) Fall-risk check 1 doc
	5	Fall-risk check 1 (includes turning) Fall-risk check 1 doc
	6	Fall-risk check 1 (includes turning) Fall-risk check 1 doc
	7	Fall-risk check 1 (includes turning) Fall-risk check 1 doc
9:00–10:00 **17.4** min available	1	NPO-ACHS 1 glucose checks NPO-ACHS 1 doc
	3	Bathing

TABLE 3.4.

TARDINESS OF FIXED-TIME TASKS IN OPTIMAL-TIMELINESS SCHEDULE FOR TEST SCENARIO.

Tardiness (min)	Number of tasks	Proportion (%)
≤ -30	28	20.4
0	14	10.2
≤ 30	95	69.3

3.4 Discussion: Research Opportunities

In exploring inpatient care work planning decisions and attempting to use an optimization model to describe the dynamics of these decisions, we found many opportunities for the OR field to support the analysis of inpatient care operations. Table 6 summarizes inpatient care work planning components that can potentially benefit from multidisciplinary research efforts. For example, visual aids traditionally used in work systems design (e.g., process maps and process charts) are useful to study and represent tasks individually but are not sufficient to characterize the dynamic and non-linear relation among tasks throughout the workday [18]. To support inpatient care work planning and execution decisions, a visual representation should illustrate the time requirements of the different types of tasks, visualize good vs. suboptimal work planning strategies, and inform work execution decisions. For example, Figs. 3 and 4 help illustrate general work requirements in terms of rounds and optimal allocation of tasks, respectively. There is still a need to include task variability and unpredictable work in this representation or to develop alternative, better graphical tools.

To support proactive inpatient care work analysis, a formal definition of unit-specific inpatient care work parameters is needed. In the case study, some of the information needed to formulate and solve the model was not readily available in a single location; data needed to be collected and analyzed, or assumptions needed to be made. Task requirements were found on an

expectations sheet for PCAs, operational metrics and objectives were identified from the literature review and direct observation of PCAs at work, and task duration estimates were obtained from pilot observational studies.

TABLE 3.5.

SPECIFICATIONS OF INDIVIDUAL STRATEGIES TO ADJUST ASSIGNMENTS WITH NO FEASIBLE SOLUTION. STRATEGY 1 CONSISTS OF DELEGATING PART OR ALL THE UNPREDICTABLE WORK TO OTHER AVAILABLE WORKERS. STRATEGY 2 CONSISTS OF DELEGATING PART OF THE PREDICTABLE WORK CONTENTS TO OTHER AVAILABLE WORKERS. STRATEGY 3 CONSISTS OF OVERTIME.

Scenario	*Strategy 1* Maximum allowance per round (min)	*Strategy 2* Predictable tasks to delegate	*Strategy 3* Number of overtime rounds needed
D	<0	Bathing 4 patients	3
F	<0	Bathing 6 patients	5
G	3.5	Bathing 3 patients	2
H	4.5	Bathing 2 patients	2
J	<0	Bathing 7 patients	6
K	<0	Bathing 8 patients	6
M	<0	Bathing 7 patients	6
N	<0	Bathing 4 patients	3
Q	<0	Bathing 10 patients	7
R	<0	Bathing 6 patients	5
S	<0	Bathing 6 patients	5

Organization and unit-specific standards that are consistent with expectations (e.g., to make patients feel ‘‘welcomed, cared for and in safe hands’’ [53], to spend time in patient education and support [54] need to be established. In addition, performance metrics that can directly guide operational, work planning decisions, and that are consistent with higher decision levels and quality goals are needed.

The relationships between operational metrics and outcomes associated with quality and safety goals need to be established. Furthermore, to reduce the need for providers to track and balance many complex and conflicting objectives while performing their jobs, it is important that possible objectives are prioritized based on their expected impact on these outcomes. At this stage, it would be useful to formally study implicit or explicit objectives that healthcare providers use to plan and execute their work and how such objectives are prioritized during a workday. In addition, it is important to identify correlations between operational metrics that can help reduce the number

of work planning objectives. Along these lines, work could potentially be designed to facilitate such correlations. For example, to ensure that timeliness is positively correlated with safety objectives, it is necessary to formally define safety needs in terms of task due-times. In the case study, the fall-risk check task was designed for this purpose; thus, the provider only needed to keep track of the timing of tasks to favor patient safety. Spatial dispersion, on the other hand, will often be negatively correlated with metrics that require several patients to be visited within a short period of time, which is an inherent aspect of inpatient care services. In such cases, spatial dispersion can be used as a secondary objective in work planning and as a primary objective in other decisions. For instance, while tasks can be assigned to rounds with the objective of minimizing tardiness, they can be executed within rounds in a sequence that minimizes distance walked, or equivalent metrics.

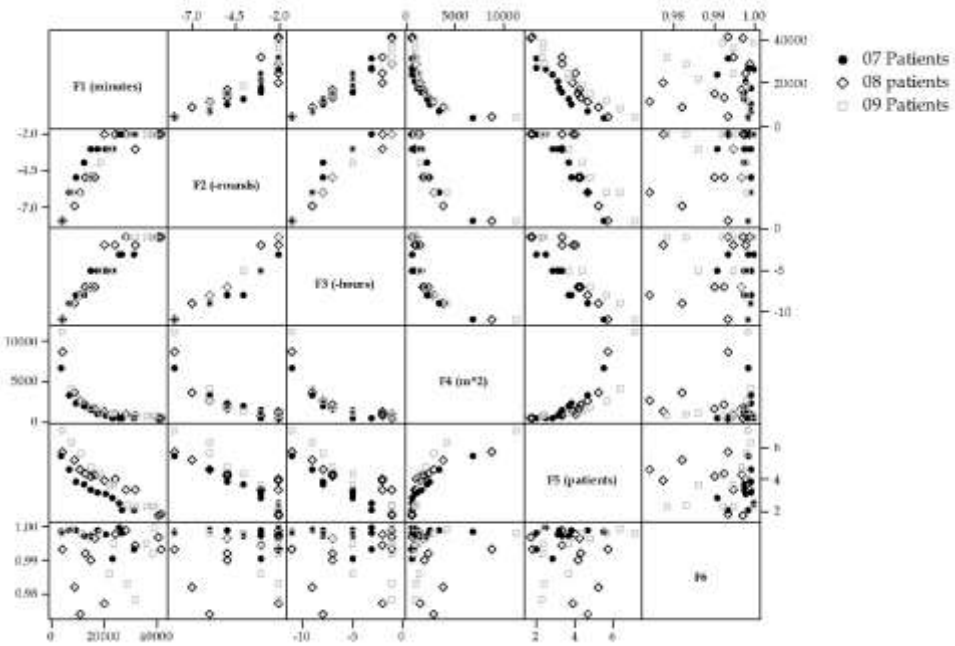

Figure 3.5. Relationship between proposed healthcare quality objectives in case study.

TABLE 3.6.

INPATIENT CARE WORK PLANNING RESEARCH AGENDA.

Research Area	Topics
Visual representation of inpatient care work:	
	Graphical tools to support inpatient care work analysis, planning and execution.
Formal specification of unit-specific work requirements:	
Inpatient care work parameters	Patient factors determining predictable tasks demand
	Standard time and variability of predictable tasks (conditional on patient factors).
	Simultaneous tasks and time savings.
	Physical and cognitive effort scores of tasks.
	Real-time, shift-specific predictable tasks list.
	Forecasting of work demand (short- or long-term).
Performance metrics and goals	Operational on-line.
	Operational off-line.
	Tactical planning.
Determination of whether a specific patient assignment is feasible:	
	Determining probability of work-arounds, requesting support, finishing all tasks during shift.
Design and evaluation of context-dependent work planning strategies:	
Defining the rounds structure	Determining recommended number of rounds and length.
	Establishing allowance per round based on unpredictable work and task time variability.
Assigning predictable work to rounds	Incorporating variability in task durations.
	Developing practical solution approach (to incorporate in IT, for easy decision-making by provider).
	Rescheduling work after plan is significantly disrupted.
	Scheduling predictable work of care teams.
Design and evaluation of context-based inpatient care work execution strategies:	
Task sequencing within rounds	Defining task priority levels (includes predictable and unpredictable work).
	Identifying optimal sequencing/resequencing strategies.
	Identifying task compression strategies
	Characterizing interruption-handling strategies (e.g., when to preempt, postpone, or resequence).

The proposed model was based on the commonly used hourly rounds. At this stage of the research, allowances were defined from the available data and verified through practitioner assessments. A larger sample is needed to validate these allowance estimates. Hourly rounds can accommodate the order of task durations in this type of environment. Nevertheless, the nature of task durations and the rounds structure can have an impact on the objective function(s) that are applicable to the problem, as well as on the ensuing work planning strategies. Systems in which task durations are

large compared to the round time may require the definition of alternative measures of timeliness. The allowance values will not only affect the assignment of tasks to rounds, but also the mathematical feasibility of the problem, which can potentially indicate the reasonableness of the associated workload and expectations. Furthermore, cognitive and behavioral sciences should be used to formally investigate the most appropriate rounds structure. It may also be the case that rounds at different times should have different durations and allowances. In fact, our preliminary analysis of unpredictable work showed that variable allowances could be needed to address unpredictable work. Allowance estimates per round ranged between 6 and 21 min. Round allowances need to be established and updated based on formal studies of task duration variability and of the demand for unpredictable tasks. Work sampling [55] and recurrent event data analysis methods [56] can be used to estimate the expected frequency and duration of unpredictable tasks throughout the workday.

Depending on the problem size and the objective criteria selected, new approaches to solving inpatient care work planning problems are needed. The proposed formulation considers deterministic time durations but in reality, such durations are subject to uncertainty. Therefore, alternative formulations and solution approaches that incorporate variability are needed. Stochastic programming and robust optimization techniques can be used to incorporate such variability in the suggested plan. Variability also implies the potential need for rescheduling each time there is a significant disruption to the initial work plan. Thus, approaches to update the work plan are needed. Rescheduling may involve slightly modifying the initial plan or simply reformulating and solving the problem with the updated parameters. In addition, there may be situations when the problem is not feasible to begin with, or becomes infeasible after disruptions (e.g., long unpredictable tasks arise, leaving insufficient time to perform the remaining tasks in the shift). In such a case, strategies

to support the worker need to be investigated. Table 5 illustrated how the model can be used to evaluate some basic strategies. More complex strategies such as task compression, i.e., dedicating less time to perform a task at the expense of increased physical or cognitive effort as well as of decreased safety, can also be investigated using an OR framework [57, 58]. Computer simulation techniques can then be used to evaluate the expected quality of work plans derived from different techniques by comparing the planned vs. simulated outcomes in the face of variability. Simulation modeling should also be used in sensitivity analysis of the robustness of strategies to variability in parameter values and patient mix, prior to implementation.

Regardless of the predictable work planning approach, a practical solution method is needed so that providers can actually implement it while caring for their patients. Ideally, the proposed model should be used to provide a work plan that is tailored to the needs of the actual patients assigned in a specific workday. In this case, ‘‘practical’’ would refer to making it easy to solve the problem (i.e., reschedule) each time there is a significant disruption to the original plan. Such disruptions may include changes in the patient mix (e.g., when a new patient is admitted or when a current patient’s needs change due to deterioration or improvement), realization of actual task durations that significantly deviate from the reference values used in the formulation, and interruptions lasting longer than the planned slack, among others. In addition, the proposed modeling approach can be used to identify and validate simple but robust work planning rules that ensure a high-quality schedule across likely workload scenarios and that can be followed by providers without the need of sophisticated computing equipment.

Although planning helps to ensure that care plans are consistent with guidelines, resources are used efficiently, and patients’ needs are addressed, such benefits will not be observed if the plan is not successfully implemented [48]. The proposed model assigns tasks to rounds leaving the

provider with the decision of sequencing the tasks within the round and handling unpredictable tasks arising during the round. Such flexibility comes at a cost; for example, it may only be possible to implement part of the recommended workday plan due to unforeseen events. At this stage, unpredictable tasks are directly addressed by placing them in the most appropriate place on the stack or queue of pending activities in the mind of a provider at a given time [26]. Stacking involves high cognitive load. The proposed approach helps to systematically define a short-term stack per round. Traditional dispatching rules could be adapted to guide task sequencing, considering both within-round and shift-long performance. Sequencing actions in the presence of unpredictable work may include the following: blocking, delegating, preempting, mediating, and postponing tasks that arise within a round [32]. Healthcare workers also have the capability of altering the time used in performing a task (i.e., task compression), but at a physical and/or cognitive cost [59, 60]. Stochastic optimization techniques could be used to study this decision. Theories from cognitive human factors [26, 61], interruption psychology [62, 63], and priority-setting in clinical nursing [64] also need to be studied and incorporated into decision support models for task sequencing and resequencing.

Finally, the model can be expanded to support other models of care used in healthcare organizations. The formulation used in this paper to illustrate the work planning decision was based on the model of ‘‘Primary Nursing’’, in which patients are allocated to a healthcare provider who is the leader in the care associated with this patient. Different modeling techniques may be needed to study work planning in environments using ‘‘Functional Nursing’’ (where tasks are distributed based on the healthcare worker expertise) or ‘‘Team Nursing’’ (in which a group of staff with different skill levels are responsible for a set of patients) [6–8].

3.5 Conclusions

This article explored inpatient care work planning decisions and proposed an optimization model as a framework to describe the associated research opportunities. Although, the results described in the case study do not directly apply to other organizations, or perhaps even to other units within the same organization, literature review findings provide some insight into the complexity of inpatient care work and the potential value of using a systematic approach to help healthcare professionals plan for their workday. The end goal should be to support healthcare providers in identifying work plans that allow them to care for their patients in a safe, timely, efficient, effective, patient-centered and equitable manner.

The modeling exercise suggests a new perspective in proactive inpatient care work planning and motivates further research on the topic. Research opportunities range from deepening our understanding of physical and cognitive capabilities of healthcare workers to analyzing infeasible, optimal, robust, and practical work plans. These challenges represent an opportunity for interdisciplinary collaboration among healthcare providers, decision-makers, human factors engineering experts, and operations researchers to push the state-of-the-art of traditional work design tools that have limited application in supporting complex work, such as that of inpatient care.

3.6 References

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CHAPTER 4

DEVELOPING PRACTICAL CONTEXT-BASED WORK PLANNING STRATEGIES FOR INPATIENT CARE

4.1. Introduction

Inpatient care is the care provided to a patient that has been admitted to a healthcare facility, such as a hospital, nursing home, among others, and requires at least one overnight stay. The focus of this study is on the dynamics of the work performed by inpatient care providers. In particular, this study focuses on the work system of patient care assistants (PCAs) in a healthcare facility unit. Usually, inpatient care workers provide a basic level of care to a specific group of patients through the execution of a set of tasks during a work period (shift). Inpatient care tasks may involve predictable tasks with specific due time or frequency requirements as well as unpredictable tasks with immediate priority [1]. Predictable tasks are known at the beginning of the shift based on the characteristics of the group of patients, while unpredictable tasks are random tasks that become part of the workload during the shift. Predictable tasks can be of two types, differentiated by the presence or absence of a requirement to perform the task at a specific time: fixed-time and frequency-based tasks. Fixed-time tasks have a specific target time (e.g., glucose checks, vitals), while frequency-based tasks have a specified frequency but no specific target time (e.g., linen change, incision care) (Chapter 3) [2]. Healthcare workers commonly use hourly rounds to organize their workday because such rounds are easy to track. Then, the short-term inpatient care work planning (SICWP) problem consists of assigning the daily predictable tasks to rounds within a shift. This SICWP problem was formulated in Chapter 3 as a variation of the 0-1 generalized assignment problem with nonlinear capacity constraints (NLGAP) [3]. The NLGAP has been

shown to be NP-complete [3]; thus, many solution approaches have been proposed during the past decades.

The formulation for the SICWP problem was described in Chapter 3. It is based on a decision variable indicating whether a specific task is assigned to a specific round. Each round has a specified available time and each task has a specified duration. Pairs of potentially simultaneous tasks are also predefined along with the potential time savings of assigning them to the same round. Constraints ensure that each task is assigned to exactly one round, that the total time of tasks assigned to each round is not higher than the available time per round, that the savings of simultaneous tasks are considered in the calculation of round task times, and that consecutive frequency-based tasks of the same type are performed with at least a specific amount of time between them. The formulation also allows for precedence requirements, which indicate that certain tasks need to be performed before some other tasks. The objective function is to minimize the total quality cost. The authors proposed several quality cost metrics and concluded that timeliness and spatial dispersion can be used to represent inpatient care delivery quality. The timeliness cost was defined as a penalty when a task was not performed at a specific time and the spatial dispersion cost was a substitute for the amount of walking necessary for the worker to perform the tasks (Chapter 3).

In actual healthcare settings, the SICWP problem needs to be solved in real time by healthcare workers during the first few minutes of their workday and adjusted, if necessary, during the rest of the shift for unpredictable tasks or variability in the duration of the tasks. Thus, there is a need to support these workers in planning their daily work while considering their human capabilities and limitations. Nevertheless, work planning strategies should still be consistent as possible with the actual characteristics of each individual workday, possibly making fixed

strategies inadequate. The objective of this chapter is to investigate practical context-based work planning strategies for solving the SICWP problem. These practical strategies should consider the boundaries of what healthcare workers can actually implement with minimal computational resources. Consequently, the strategies need to be evaluated in terms of their cognitive complexity in addition to the quality of health care delivered.

The chapter is organized as follows: Section 4.2 reviews the literature on approaches to solve the NLGAP and to measure the cognitive complexity of human-implemented heuristics. Section 4.3 describes the proposed methodology to develop a unit-specific practical heuristic and to evaluate its cognitive complexity and performance. Section 4.4 discusses an application of the methodology to a specific inpatient care work system. Section 4.5 presents discussion and future research.

4.2. Literature Review

4.2.1. NLGAP Solution Approaches

To gain insight into how to support healthcare workers in solving the SICWP problem, the study started by exploring approaches to obtain the optimal solutions to the NLGAP. An initial literature review was conducted by searching the databases Business Source Complete and Science Direct. The keywords used in different combinations were as follows: nonlinear, 0-1 programming, 0-1 integer programming, binary programming, generalized, assignment, allocation, capacity, constraint and knapsack. The search dates were established from August 1988 to March 2019. Only articles from peer-reviewed journals published in the English language were included in the review. The search resulted in two solution approaches to solve the NLGAP: an exact algorithm and a heuristic [3].

Given the limited number of studies presenting an application or proposing a solution algorithm for the NLGAP, the literature review was expanded to identify proposed methods to

solve the GAP. The same databases were searched using the same conditions, except for the keywords: generalized, assignment, problem, applications, knapsack, approximation, exact, metaheuristic, algorithm, and integer programming. Different solution approaches for the GAP have been proposed for more than three decades [4-7]. Recent work on exact methods included branch and bound methods [8, 9], branch and price methods [10, 11] and branch-and-cut-and-price algorithms [12]. Heuristics included metaheuristics and approximate algorithms. Metaheuristics included tabu search [13, 14], simulated annealing [15], genetic algorithms [16], path-relinking [17, 18], ant system [19], and variable depth search heuristics [20, 21]. Approximate algorithms include lagrangian relaxation-based heuristics [22, 23], polynomial time approximation algorithms [24], greedy heuristics [25, 26, 27], set partitioning heuristics [28], and linear programming relaxation-based heuristics [29]. There are also hybrid heuristics, which consist of the combination of different approaches [30, 31]. Because the GAP is a computationally intractable problem (NP-complete) [32], most of these solutions are based on algorithms that require computational resources to be implemented in a reasonable amount of time.

Among the different types of solution algorithms for the GAP, the greedy heuristics could potentially be more intuitive and more suitable for the human capabilities and limitations of the PCA. Thus, greedy heuristics were studied as a starting point in the identification and development of a practical solution approach. Therefore, the literature review was refocused to identify greedy heuristics to solve the GAP. The same databases were searched using the same conditions, except for the keywords: generalized, assignment, problem, knapsack, greedy, heuristic, algorithm, and integer programming. Three studies proposing different greedy heuristics were identified from the search. The greedy heuristic proposed by [25] was outperformed by the heuristic approach proposed by [33] when the duration of the tasks are independent of the round to which they are

assigned. The comparison was based on CPU time, the number of optimal solutions, and the proximity to optimality of the solutions. Further, the approach proposed by [33] has smaller time complexity when compared with [25], O(mn log n) and O(n!+n), respectively. Another greedy heuristic was proposed by [34] based on the solution proposed by [25]; however, this study did not present a numerical comparison with previous greedy heuristics.[34] used a family of weighted pseudo-cost functions that included a parameter that would need to be defined for each problem, which increases the complexity of the method. Moreover, [34] required more computational time than the other two greedy heuristics reviewed, its time complexity is O(nm+3 log n). Based on the performance evaluation results reported in the literature and the practicality of the algorithm, the approach proposed by [25] was selected as the starting point to develop practical heuristics to the SICWP.

4.2.2. Evaluating Cognitive Complexity

In human factors engineering, complex cognitive systems (such as healthcare systems) are settings where the knowledge and cognitive strategies employed by workers are the causes of variability in their behavior [35, 36]. In these complex cognitive systems, the worker's performance is determined by the mental workload he or she experienced while executing the work [37]. According to Wickens [38-40], the workload demand of an individual is processed through the following resources: visual perception, auditory perception, cognitive, fine psychomotor response, gross psychomotor response, speech response, and tactile response [56-58]. Since the focus of this study is the evaluation of the practical heuristic in terms of the cognitive component of the workload experienced by the PCA while planning for work, methods or techniques to assess mental workload were revised.

Over the years, several techniques have been used to assess workload in complex cognitive systems [37, 41, 42]. Lately, four main categories have been used to group the techniques: subjective-empirical, objective-empirical, subjective-analytical, and objective-analytical [42].

Empirical techniques to assess workload are the most common in the literature. In these types of techniques, the information to assess the workload is gathered from individuals while performing a task or after performing a task [37]. Empirical techniques can be either subjective or objective. Subjective-empirical techniques usually gather information from individuals' opinions (e.g. worker or operator) through self-report questionnaires (surveys), interviews, or rating scales [37, 42]. Common examples of these techniques are the NASA-TLX [43], SWAT [44], and Modified Cooper-Harper [45]. Although they have been widely used, these tools are subject to memory biases because they do not provide real-time feedback (e.g., workers fill out the surveys after performing the tasks) [42]. Objective-empirical techniques attempt to gather information directly from the individual by measuring a variable representing the workload of that worker. These techniques are less developed than the subjective-empirical techniques [37], but they rely on facts rather than opinions. Two sub-categorizations of objective-empirical techniques are performance measures and psycho-physiological state techniques. Performance measures techniques base workload assessment on measurements of the worker's behavior (e.g. primary task and secondary tasks measures) [37]. Psycho-physiological state techniques base the workload assessment on measurements of physiological metrics associated with the cognitive task of interest while the worker is performing the task [37]. Some examples include the measurement of brain activity using electroencephalography and cardiovascular activity through heart rate, among others [46]. Several advantages and disadvantages of these objective-empirical techniques were discussed in [46].

Although empirical techniques to assess workload are the most common in the literature, they cannot be used in early stages of the design prior to implementation because no individuals could perform the tasks [42]. Since this research corresponds to an early stage of a design, the focus becomes the analytical techniques. Analytical methods can predict workload in the design stage as well as evaluate an already designed and implemented system [37].

Subjective-analytical measures are based on expert opinion. These types of workload assessments have been used mainly in sectors other than academia [42]. Some examples of these techniques are projective application of SWAT [47] and the projective Pro-SWORD method [48].

The objective-analytical methods include mathematical models, simulation models, and task analysis methods [37, 42]. Among the mathematical models, two of the most recently used models are those based in control theory and queuing theory. Mathematical models based on control theory focus on evaluating the worker's performance in order to eliminate errors or deviations from a defined path. An example of these models is the Procedure-Oriented Crew Model (PROCRU) [49]. However, these techniques are restricted to systems that involve continuous controlling tasks [37]. Mathematical models based on queuing theory consider the worker as a server with limited attention resources. Tasks arrive to be processed individually by the single server. These techniques have been applied to man-machine modeling when there is no concurrent processing [37]. Although mathematical models are independent of the domain, they are considered static to some extent [50]. Simulation models are based on task analysis and the statistical characteristics of the system's parameters [37]. Although simulation models are considered the most complete techniques among the analytical techniques, these models require information about the parameters of the system [37]. Since the design of the SICWP problem is

still in an early stage of design, detailed information regarding the parameters of the system is not available.

Among the analytical techniques, the task analysis methods are the most common [37]. Although these methods share the same name with the TA methods, they are different. The task analysis methods, described in this paragraph, are objective-analytical tools to assess workload in complex cognitive systems that are based on a detailed analysis of tasks. Also, task analysis methods are considered the most appropriate for quantitative prediction of mental workload in complex dynamic systems, second only to simulation models [37, 50]. These techniques are based on the decomposition of tasks into basic units that can be arranged sequentially; these basic units of tasks are then evaluated and assigned a corresponding workload rating value [50]. Among these techniques are Task Analysis/Workload (TAWL) [51], Time-Line Analysis and Prediction (TLAP) [52], and Workload Index (W/INDEX) [53], and the Visual Auditory Cognitive Psychomotor model (VACP) [54]. A comparison of the last three techniques indicated that all of them were effective predictors of performance [55]. Also, the ratings of techniques TAWL, TLAP, W/INDEX were based on the VACP ratings [50]. Besides the advantages of the analytical techniques over the empirical techniques, the VACP model uses “verbal anchors” to allow objectivity and consistency in the assignment of the rating values [46]. VACP has been considered one of the most reliable techniques to predict workload [56].

Since the focus of this research is the evaluation of the cognitive complexity of the unit-specific practical heuristic that needs to be implemented by the PCA, the VACP technique was selected. The technique is based on the multiple resources theory proposed by Wickens [38-40]. According to this theory, the workload demand of an individual is processed through a finite set of resources with limited capacity such as those needed for cognitive tasks. The VACP technique

allows the measurement of the overall workload for a particular instance in time as well as the measurement of the total workload experienced by the worker [56]. In this study, the technique is used to obtain measurements of the workload's cognitive component. These measurements are considered predictive because they are conceptual or analytical in nature.

4.3. Methodology

In this research, a methodology to develop unit-specific practical heuristics for inpatient care workers to solve the SICWP problem is proposed. The approach is illustrated based on the work system of PCAs in a cardiology unit.

4.3.1. Developing a Practical Heuristic for the SICWP Problem

The proposed methodology to develop a unit-specific practical heuristic (see Figure 4.1) builds on an analysis of the characteristics of the specific inpatient care unit and the analysis of optimal solutions for the SICWP problem for a variety of workload scenarios.

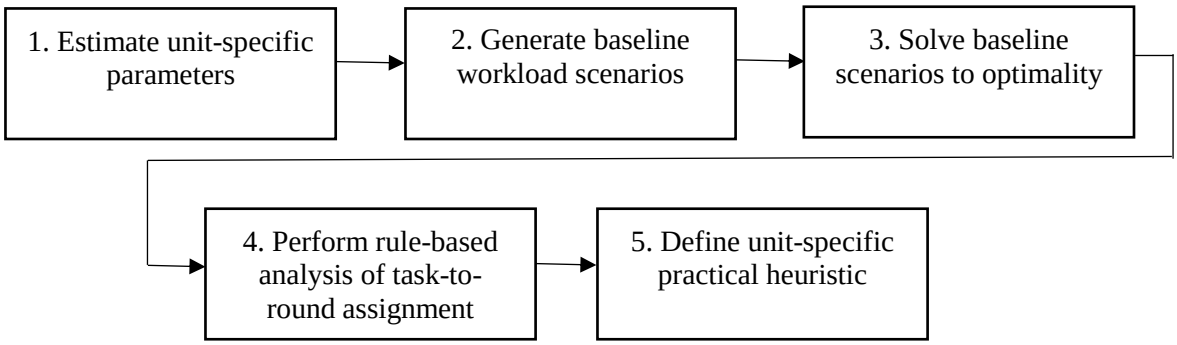

Figure 4.1. Flow chart of the steps used to develop the unit-specific practical heuristic.

- Step 1. Estimate unit-specific parameters

The following parameters need to be estimated to characterize the PCA's work in the unit: explicit and observable categorization of patient classes, physical layout of the unit and possible task locations, functions mapping classes of patients to task demands, task durations conditional

on patient class, minimum time between frequency-based tasks, and due time and release time for fixed-time tasks. The data to estimate these parameters and establish patient to task mapping functions can be collected from documented procedures, direct observation of the inpatient care workers performing their tasks, and eliciting experts' assessments from inpatient care workers themselves or supervisors and managers.

- Step 2. Generate baseline workload scenarios

A sample of baseline scenarios is generated based on the unit-specific parameters. The baseline scenarios are defined by random but feasible combinations of patients of different classes. Then each patient assignment is translated into the corresponding task demands using the established patient-to-task mapping functions and information on task durations.

- Step 3. Solve baseline scenarios to optimality

The ideal (optimal or near-optimal) schedule for each baseline scenario is obtained using the SICWP problem formulation, the desired quality metric(s), and the preferred solution approach using available computational resources (Chapter 3).

- Step 4. Perform rule-based analysis of optimal solutions

Once the ideal work plans are available, association analysis is performed to identify frequently occurring patterns related to task-to-round assignments across the different scenarios.

In association analysis a pattern is also known as an association rule, which represents an implication of the form if X then Y [57, 58]. In this study, the analysis of the SICWP problem attempts to discover interesting patterns between a task and the round where the task is assigned in optimal work plans. The analysis, originally designed to be used with large data sets, was adapted to fit the relatively small number of attributes and transactions (e.g., task-to-round assignment per scenario-patient).

Confidence and support, based on probability and statistics theory, are among the most common measures used to identify the best association rules based on their strength [57, 59]. Since the SICWP problem has a data set with skewed support distribution, only confidence was used in the analysis [57, 59]. Using confidence, which "measures the reliability of the inference made by a rule" [57], potentially useful association rules are selected based on a threshold defined by the user. In this study, characteristics of the particular inpatient care unit are considered in the definition of the threshold for the confidence measure named minconf.

The following association rules are the focus of analysis for the optimal-timeliness work plans:

- Rules that specify the assignment of each frequency-based task to a specific round. Rules with higher confidence values will indicate the consistency of assigning the corresponding round end time as the frequency-based task's due time.
- Rules that specify the assignment of a fixed-time task to a different round than the round containing its due time. Rules with higher confidence values will indicate the usefulness of assigning fixed-time tasks to an early or late round. An early round is defined as a round with an end time earlier than the task due time. Similarly, a late round is defined as a round with end time later than the task due time.

The set of rules that meet the user's criteria become the accepted rules that specify the due times for all frequency-based tasks and the portion of fixed-time tasks that should be assigned to an early or late round.

- Step 5. Define unit-specific work planning heuristic

Accepted rules are summarized and become the foundation of a unit-specific practical heuristic. All frequency-based tasks are assigned a due time to be used in guiding work planning

by assigning each task to the round with an end time closest to its (assigned) due time. Most fixed-time tasks are assigned to the round with an end time closest to its due time.

4.3.2. Cognitive Complexity Analysis

The VACP method [54, 60] is used to compare the unit-specific practical heuristic with the status quo approach in terms of cognitive complexity. The cognitive complexity of the unit-specific practical heuristic is thus assessed through the quantification of the overall workload for a particular instance in time and the total cognitive workload experienced by the PCA when creating the work plan. A VACP value above eight, in a half second period, indicates overload for the worker [60]. The following assumptions are considered in the quantification of the cognitive workload:

- The *mission* is defined as solving the SICWP problem at the beginning of the shift.
- *Functions* are defined to match the steps of the unit-specific practical heuristic or status quo approach.
- Functions are decomposed into *tasks*.
- *Tasks* are decomposed into *basic units of tasks* to be performed sequentially.
- Each time instant contained no more than one basic unit of tasks.
- Shift information is available either in print form or an electronic file(s), but no computational resources were available to solve the SICWP problem.
- The scales provided by Rusnock and Borghetti [46] are used to assign the workload ratings.

4.3.3. Evaluating Performance

Once the unit-specific practical heuristic is developed, its performance can be evaluated in a somewhat realistic environment using a Monte Carlo simulation. The Monte Carlo simulation provides measures of quality for each work plan while incorporating the variability in task duration

and random interruptions. In this research, the proposed unit-specific practical heuristic was benchmarked against the optimal and status quo approaches in terms of the unit-specific quality metrics such as: timeliness, tardiness, earliness, and distance walked.

Timeliness in round t ($t \in T$), named $Timeliness_t$, was defined as the sum of tardiness and earliness for all tasks completed in round t (see Eq. 4.1). The tardiness of task i ($i \in I$) in round t, named $Tardiness_{it}$, was defined as the difference between the completion time (c_i) and the due time of task i (d_i) (see Eq. 4.2). The earliness of task i, named $Earliness_{it}$ was defined as the difference between the completion time and the release time of each task i (r_i) (see Eq. 4.3). Timeliness per shift is defined as the sum of timeliness of all rounds t ($t \in T$).

$$Timeliness_t = \sum_{i \in I} Tardiness_{it} + \sum_{i \in I} Earliness_{it} \; \forall t \in T \tag{4.1}$$

$$Tardiness_{it} = \sum_{i \in I} c_{it} - d_{it} \; \forall t \in T \tag{4.2}$$

$$Earliness_{it} = \sum_{i \in I} c_{it} - r_{it} \; \forall t \in T \tag{4.3}$$

Distance walked in round t ($t \in T$) was defined as the distance walked for the provider in round t. In each round the distance walked by the provider is calculated as the sum of the distances between the locations of consecutive tasks. Distance walked per shift is defined as the distance walked for the provider in all rounds t ($t \in T$). This metric was an indirect representation of the provider's workload.

Since the SICWP problem formulation proposed in Chapter 3 included a constraint set that considers an allowance or slack per round to address task durations variability and unpredictable work, the practical heuristic was also evaluated in terms of the actual slack time of round t. This

metric is defined as the difference between the end time of round t (a_t) and the completion time of round t (C_t) (see Eq. 4.4). Additionally, the practical heuristic was also evaluated in terms of the planned slack time of round t, which is defined as the difference between the time available in round t and the actual busy time of round t while performing only the planned tasks (see Eq. 4.5).

$$Slack\ time\ (Actual)_t = a_t - C_t$$

$$Slack\ time\ (Planned)_t = (a_t - s_t) - \max\begin{cases} C_t - a_{t-1} \\ C_t - C_{t-1} \end{cases} \tag{4.5}$$

All quality metrics were calculated per each replicate-scenario combination and then averaged per each scenario.

4.4. Case Study

The proposed methodology is illustrated based on the work system of PCAs in a cardiology unit. PCAs perform work during twelve-hour shifts and use hourly rounds.

Currently, PCAs in the unit plan their workday by performing all fixed-time tasks before their due time and scheduling frequency-based tasks at specific times based on individual experience. In case the duration of the assigned tasks exceeded the available round time, fixed-time tasks take priority, then frequency-based tasks. Any variability is addressed upon execution. In this study, this fixed strategy is named the *status quo* approach.

4.4.1. Developing a Practical Heuristic – Case Study

The results of the implementation of the method described in section 4.3.1 to the cardiology inpatient care unit are the following:

Step 1.

Data on PCA's work system parameters were obtained in a different study [61]. The PCAs in the unit can perform up to eighteen unique types of predictable tasks, depending on the factors of the patients assigned. For this particular unit, observable patient factors that can help determine the demand for predictable tasks included medical orders for vital sign checks (e.g., every four hours), NPO (nothing by mouth), AC/HS blood glucose checks, and incision care. Other type of observable patient factor included the level of functional independence of patients (e.g., patients with bedrest). The data included a list of tasks associated with each patient factor.

Step 2.

Each baseline scenario was generated considering a random number of four to seven patients. Each patient was assigned a set of patient factors randomly generated. The feasible combinations of patient factors were twenty-one baseline scenarios (see Table 4.1). The baseline scenarios included between 122 and 146 fixed-time tasks and between 12 and 36 frequency-based tasks.

Step 3.

The optimal solutions (work plans) to the baseline scenarios were obtained using the formulation described in Chapter 3 CPLEX for MATLAB version 12.6.3. The model implementation assumed that each round involves 50 minutes of available effective time and that the remaining 10 minutes are used to anticipate variability in actual task durations as well as unpredictable work. Based on our prior analysis in Chapter 3, the preferred performance metrics to guide inpatient care work planning decisions in the collaborating unit include timeliness and spatial dispersion. The latter was considered a surrogate metric for the distance walked by the provider during the shift.

TABLE 4.1.

OBSERVABLE PATIENT FACTORS - BASELINE SCENARIOS

	Total patients	Patients with Vitals Q6	Patients with Vitals Q4	Patients with NPO	Patients with ACHS	Indep. Patients	Non-Indep. Patients	Patients with Bedrest	Patients with Incision Care
Max.	7	7	6	3	3	7	7	3	7
Min.	4	0	0	0	0	0	0	0	0
Avg.	5.6	2.6	3.0	2.0	2.0	1.8	3.9	1.9	3.0
SD.[a]	1.2	2.4	2.0	1.1	1.1	2.4	2.2	1.1	2.1

[a]Standard deviation.

Optimal work plans for timeliness and spatial dispersion costs were obtained separately (see Table 4.2). The running time of the optimal-timeliness and optimal-spatial dispersion solutions for each scenario was on average 54.7 and 67.8 seconds, respectively. The optimal-timeliness solutions for 81% of the scenarios were optimal, while the rest of the scenarios had a 1.5% or lower gap. The optimal-spatial dispersion solutions were obtained in less than four iterations. The k-means algorithm, proposed in Chapter 3, was stopped when the objective function decreased by less than or equal to five (AutoCAD) units in relation to the previous optimal-spatial dispersion value. The five units were used to represent a small value in relation to the initial and last spatial dispersion values. The results showed that the five units were on average 0.01% of the spatial dispersion in the first iteration and 8.88% of the spatial dispersion in the last iteration. For all scenarios, the solution was optimal in each iteration.

Step 4.

The resultant optimal-timeliness wok plans were analyzed to identify patterns related to task-to-round assignment. Frequency-based tasks and fixed-time tasks were analyzed separately.

TABLE 4.2.

OPTIMAL SOLUTIONS FOR BASELINE SCENARIOS

	Optimal-timeliness		Optimal-spatial dispersion	
Scenario	Timeliness[a] (min)	GAP (%)	Spatial dispersion (m^2)	GAP (%)
1	3,630	0	827.2	0
2	3,210	0	954.5	0
3	3,450	0	3266.8	0
4	3,750	0	3604.4	0
5	3,750	0	957.1	0
6	3,210	0.85	841.9	0
7	3,150	0	861.5	0
8	2,370	0	1822.7	0
9	2,730	0	260.8	0
10	3,150	0	298.5	0
11	1,890	0	389.7	0
12	2,310	0.98	621.8	0
13	2,790	0	514.0	0
14	2,130	0	572.1	0
15	2,550	0	543.6	0
16	2,970	0.74	578.3	0
17	2,430	1.42	143.4	0
18	2,850	0	313.0	0
19	3,270	0	814.3	0
20	2,490	0	143.4	0
21	2,850	0	313.0	0

[a] Fixed-time tasks timeliness

Frequency-based tasks analysis based on optimal-timeliness work plans: The possible rules were ranked, and those with the highest values were compared against the confidence threshold (see Table 4.3). In this study, significant association between specific frequency-based tasks and rounds was evaluated using the confidence threshold of 80%.

TABLE 4.3.

RULES OF ASSOCIATION OF FREQUENCY-BASED TASKS TO ROUND ASSIGNMENT, 4 TO 7 PATIENTS

Rule	Confidence (%)
Update board → Round 1	95.7
Incision care → Round 1	100.0
Linen Change → Round 2	56.5
Lunch break → Round 3	100.0
Break period 1 → Round 2	100.0
Break period 2 → Round 4	100.0
Walk 1 → Round 1	100.0
Walk 2 → Round 3	100.0
Walk 3 → Round 5	100.0

All rules had significant association, except for the rule related to the frequency-based tasks named "linen change". Since the confidence of the "linen change→round 2" rule was below the minconf, the association analysis for this particular frequency-based task was performed per number of patients. The resultant rules were ranked, and those with the highest values were compared against the threshold. A minconf of 80% validated the rule to assign all tasks named "linen change" to Round 1 whenever the unit had four patients. On the other hand, the rules (with the highest confidence value) for five, six, and seven patients could not be validated with the current minconf. However, these three rules indicated the assignment of "linen change" to Round 2. Considering that the heuristic for the PCA needed to be as practical as possible (so the PCA can solve the assignment problem with minimal resources), the number of rules needed to be small. Thus, a more detailed analysis was discarded and the rules for five to seven patients were integrated into one rule. Consequently, two rules were selected for linen change: one rule for up to four patients and one rule that applied to five to seven patients (see Table 4.4).

TABLE 4.4.

RULES OF ASSOCIATION OF FREQUENCY-BASED TASKS TO ROUND ASSIGNMENT PER NUMBER OF PATIENTS

Numb. patients	Confidence (%)	Rule
4	87.5	Linen Change → Round 1
5-7	66.7*	Linen Change → Round 2

* Minimum value obtained among 5, 6, and 7 patients.

The selected rules for all frequency-based tasks were consolidated in Table 4.5, where each frequency-based task was assigned a due time equal to the end time (a_t) of the rule's round. At this stage of the analysis, all the frequency-based tasks were assigned due times based on the results of the association analysis.

Since the PCA in this particular case study ate lunch around noon, the selected rule for lunch breaks was adjusted, assigning round 6 instead of round 3 (optimal assignment). Similarly, break periods 1 and 2 were reassigned to rounds 3 and 6 to distribute them evenly in the shift, which was the current practice in the particular case study.

A similar analysis per number of patients (four to seven) presented similar results: approximately 70% were assigned to an on time round, and the rest were assigned to an early round.

Fixed-time tasks analysis based on optimal-timeliness work plans: The analysis of the work plans obtained for the baseline scenarios indicated that fixed-time tasks were assigned most frequently to an early or on time round (see Table 4.6). Approximately 0.2% of fixed-time tasks were assigned to a later round, so this case is omitted from the analysis. Considering an 80% threshold for confidence, none of the rules were selected.

TABLE 4.5.

FREQUENCY-BASED TASKS WITH DUE TIME – PER NUMBER OF PATIENTS

Numb. patients	Rule	Task due time
any	Update board → Round 1	60
any	Incision care →Round 1	60
4	Linen Change → Round 1	60
5-7	Linen Change → Round 2	120
any	Lunch break → Round 3	180
any	Break period 1 → Round 2	120
any	Break period 2 → Round 4	320
any	Walk 1 → Round 1	60
any	Walk 2 → Round 3	180
any	Walk 3 → Round 5	300

TABLE 4.6.

RULES OF ASSOCIATION OF FIXED-TIME TASKS TO ROUND ASSIGNMENT, 4 TO 7 PATIENTS

Confidence (%)	Rule
71.3	Fixed-time tasks → On time Round
28.4	Fixed-time tasks → Early (-1) Round
0.2	Fixed-time tasks → Late (+1) Round

Early (-1): on time round -1 ; Late (+1): on time round +1

A second association analysis for fixed-time tasks was perform per type of fixed-time task (see Table 4.7). Tasks with due times in round 1 were excluded. A minconf of 80% validated the rule to assign all tasks named “NPO 1 glucose checks” to an early round. The other three rules could not be validated with a minconf of 80%. Considering that the heuristic for the PCA needs to be as practical as possible, the number of rules needed to be small. An integration of the four rules into one rule considered that a proportion from 20% to 88.9% of these fixed-time tasks were assigned to an early (-1) round. Therefore, we considered the average of the proportions (55%) of these

fixed-time tasks to be the rule of assignment for an early round. In practical terms, the rule consisted of assigning to a round approximately half of the fixed-time tasks that are due in the next round.

TABLE 4.7.

RULES OF ASSOCIATION OF FIXED-TIME TASKS TO ROUND ASSIGNMENT

Confidence (%)	Rule
56.8	Q4 Vitals & doc → On time Round
68.8	Q6 Vitals & doc → Early (-1) Round
79.3	TEMP 1 rounds → On time Round
88.9	NPO 1 glucose checks → Early (-1) Round

Step 5

In practical settings, the PCA will solve the SICWP problem at the beginning of the shift based on the following summary of the rules obtained in the previous step:

- Rule 1: Assign all frequency-based tasks to a specific round according to the due times obtained in Table 4.5 ("ideal due times").
- Rule 2: Assign approximately half of the fixed-time tasks that are due in the next round to the current (early) round.

In Chapter 3 it was identified that the number of rounds containing tasks associated with the same patient was smaller for the optimal-spatial dispersion work plans than the optimal-timeliness work plans regardless of the type of task, the following rule is added:

- Rule 3: While performing rule 2, whenever possible, assign to the same round tasks corresponding to the same patient.

The above rules became the foundation of the practical heuristic for the cardiology inpatient care unit (see Figure 4.2). The practical heuristic was designed with minimizing timeliness as the primary objective; spatial dispersion was considered as a secondary objective whenever possible. It is assumed that the PCA will execute the work plan minimizing the distance walked whenever possible.

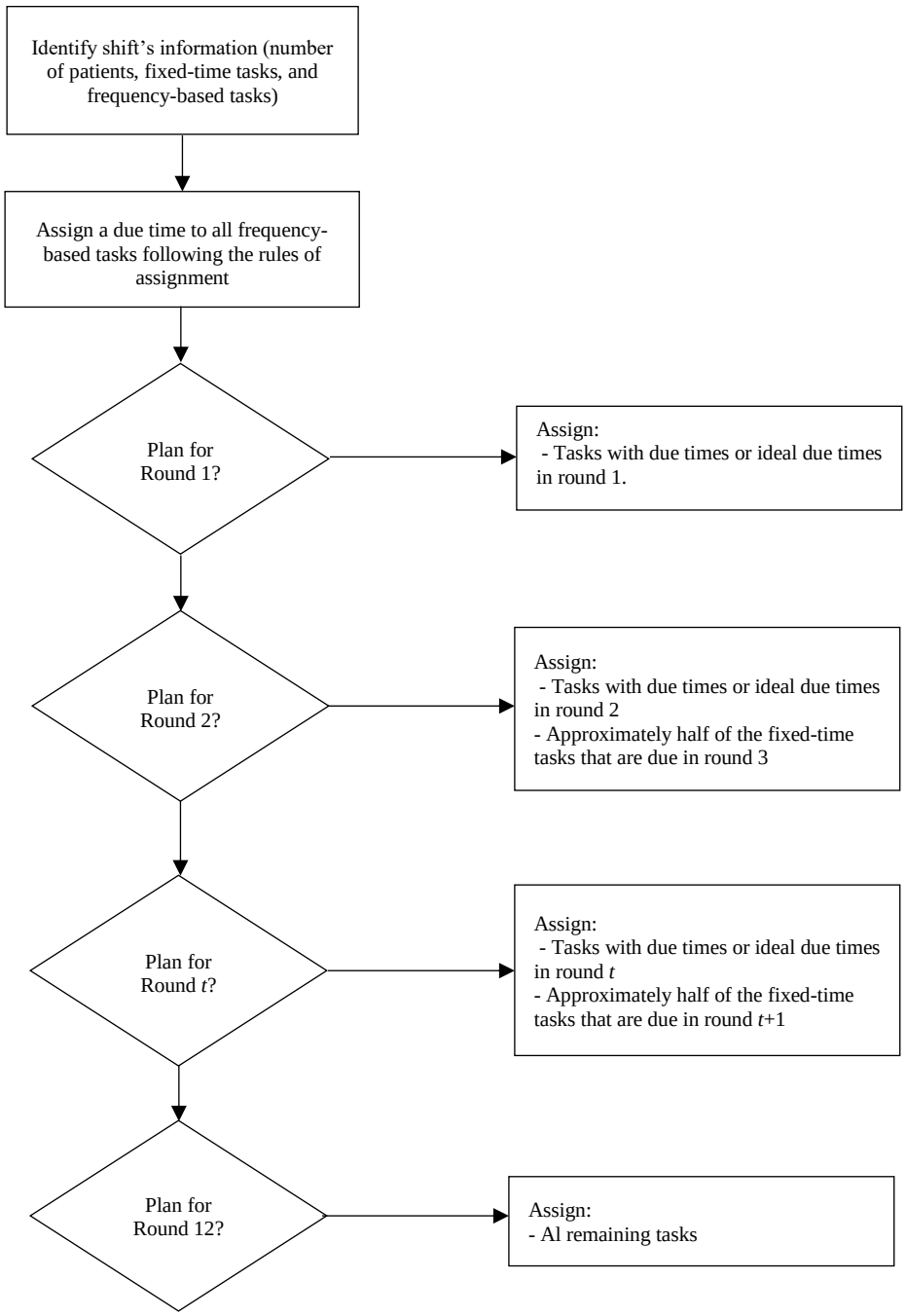

Figure 4.2. Flow chart for the practical heuristic (cardiology unit).

4.4.2. Cognitive Complexity Analysis – Case Study

Table 4.8 shows the results of the cognitive workload quantified for the practical heuristic and the status quo approach using the VACP method. The total predicted cognitive workload for the status quo approach and practical heuristic were 37.6 and 56.5, respectively (see Table 4.8). In both approaches, the predicted cognitive workload for each particular instance indicated that the PCA did not exceed the threshold (see Table 4.8, column Overload).

On the other extreme, since the optimal solution approaches require computational resources to be solved, they cannot practically be analyzed in terms of human cognitive complexity. However, as an attempt to approximate the number of functions that need to be performed to solve the problem, it was assumed that the healthcare provider solved the problem by comparing all possible solutions. All different possible arrangements of the tasks (with n as the number of tasks) in the shift could be considered an upper bound for the number of all possible solutions for the SICWP problem. In that case, the healthcare provider had to repeat n! times all the necessary steps to find each solution. A better approximation could consider only fixed-time tasks, on average 62% of the total number of tasks, which would result in a smaller number of possible solutions; however, this approximation would still require a large number of functions compared to the number of functions necessary to perform the practical heuristic and status quo approach (between 9.8x10202 to 1.2x10254). Therefore, the complexity of the practical heuristic is somewhere between the complexity of the status quo and the optimal solution approaches, but falls closer to the status quo approach, which was the objective in the design stage.

TABLE 4.8

VACP WORKLOAD ASSIGNMENTS FOR THE SICWP PROBLEM

Status Quo			
Function	Task Activity	Cognitive	Overload
Access shift information	Select information	1.2	no
Assign due time to a frequency-based task (knowledge-based/memory)	Select frequency-based task	1.2	no
	Attribute due time (knowledge/memory)	5.3	no
	Register due time	5.3	no
Assign fixed-time task (on time)	Select fixed-time task	1.2	no
	Find fixed-time task due time	1.2	no
	Select round	4.6	no
	Register round	5.3	no
Assign frequency-based task (on time)	Select frequency-based task	1.2	no
	Find frequency-based task due time	1.2	no
	Select round	4.6	no
	Register round	5.3	no
	Total cognitive workload	37.6	

Proposed Heuristic			
Function	Task Activity	Cognitive	Overload
Access shift information	Select information	1.2	no
Assign due time to a frequency-based task (ideal chart)	Select frequency-based task	1.2	no
	Find frequency-based task/Numb. patients (ideal chart)	6.8	no
	Register due time	5.3	no
Assign fixed-time task (on time)	Select fixed-time task	1.2	no
	Find fixed-time task due time	1.2	no
	Select round	4.6	no
	Register round	5.3	no
Assign frequency-based task (on time)	Select frequency-based task	1.2	no
	Find frequency-based task due time	1.2	no
	Select round	4.6	no
	Register round	5.3	no
Assign fixed-time task (ahead of time)	Evaluate assignment	7	no
	Select fixed-time task	4.6	no
	Find fixed-time task due time	1.2	no
	Select round	4.6	no
	Register round	5.3	no
	Total cognitive workload	56.5	

4.4.3. Evaluating Performance – Case Study

In order to evaluate the practical heuristic performance in terms of the unit-specific quality metrics, 21 test scenarios were simulated. These test scenarios were generated between seven to ten patients, with patient factors selected randomly. The patient factors defined the type and number of tasks per scenario. The test scenarios considered for the Monte Carlo simulation included only feasible optimal solutions.

Exponentially distributed task durations with a specified mean based on the unit-specific parameters were used in the simulation. Earliest Due Date (EDD) was the dispatching rule used to sequence the tasks within rounds regardless of the solution approach. Interruptions occurred randomly throughout the shift, and in each interruption the healthcare provider engaged immediately. The interruption lag (time to engage an interruption task) was considered as 20% of the elapsed duration time of the primary task, and the resumption lag was considered as 10% of the remaining duration time of the primary task. Each combination of scenarios and work plans was replicated 30 times using a simulator developed with Excel Visual Basic for Applications (VBA) [62].

The performance of the optimal and status quo approaches were used as benchmark for the analysis of the practical heuristic in terms of the following quality metrics: timeliness, tardiness, earliness, and distance walked.

In terms of timeliness, even though the average of the simulated runs seemed to indicate that the practical heuristic was better (lower) than the status quo approach in about half of the scenarios (67%), there was no significant difference between them (see Figure 4.3). In fact, the optimal-timeliness approach had significantly better timeliness than the practical heuristic for less than half of the scenarios. Specifically, there were no significant differences between optimal-

timeliness approach and the practical heuristic for scenarios S3, S4, S6, S7, and S9. Similarly, the optimal-timeliness approach had significantly better timeliness than the status quo approach for about half of the scenarios (56%). Specifically, there were no significant differences between optimal-timeliness and the status quo approaches for scenarios S4, S6, S7, and S9.

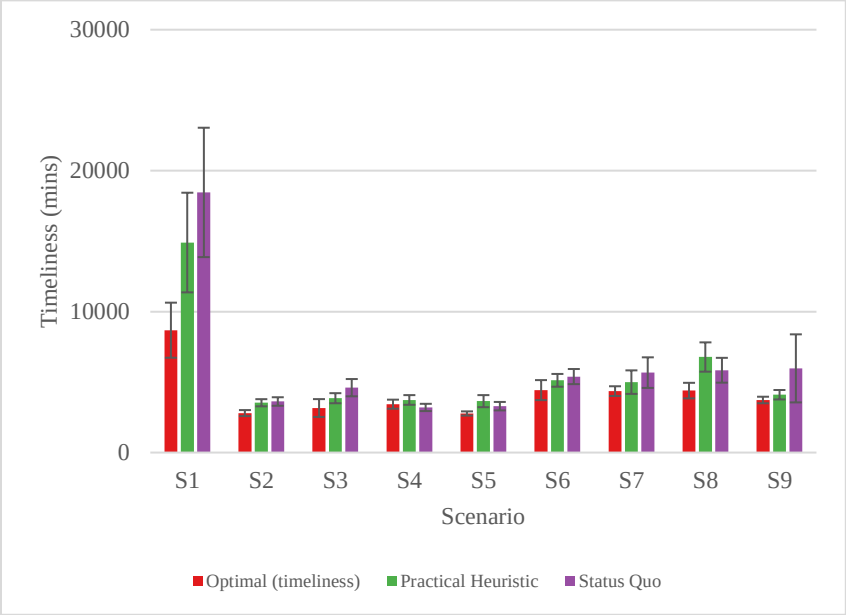

Figure 4.3: Average timeliness per shift.

The main component of timeliness was due to tardiness, with a smaller relative contribution due to the earliness component for all the solutions. The tardiness component averaged 96% of timeliness for all scenarios. The difference in magnitude of these components is illustrated using the cumulative tardiness and earliness for a particular scenario S3 (see Figure 4.4). The small contribution of earliness in the timeliness measure was expected because the timeliness cost used in the optimization did not include the release time. Thus, the rest of the results analysis focused on the tardiness metric.

In terms of tardiness, the average indicated that the practical heuristic was better (lower) than the status quo approach in almost all scenarios (89%) (see Figure 4.5). Considering the

variability of the results, the practical heuristic was significantly better than the status quo approach for about half of the scenarios. There were no significant differences between the practical heuristic and the status quo approach for scenarios S1, S5, S7, and S8. Also, even though the average seemed to indicate that the optimal-timeliness approach was better than the practical heuristic for all the scenarios; it was significantly better than the practical heuristic for about half of the scenarios (67%). Also, all the approaches were better than the optimal-spatial dispersion approach in terms of tardiness.

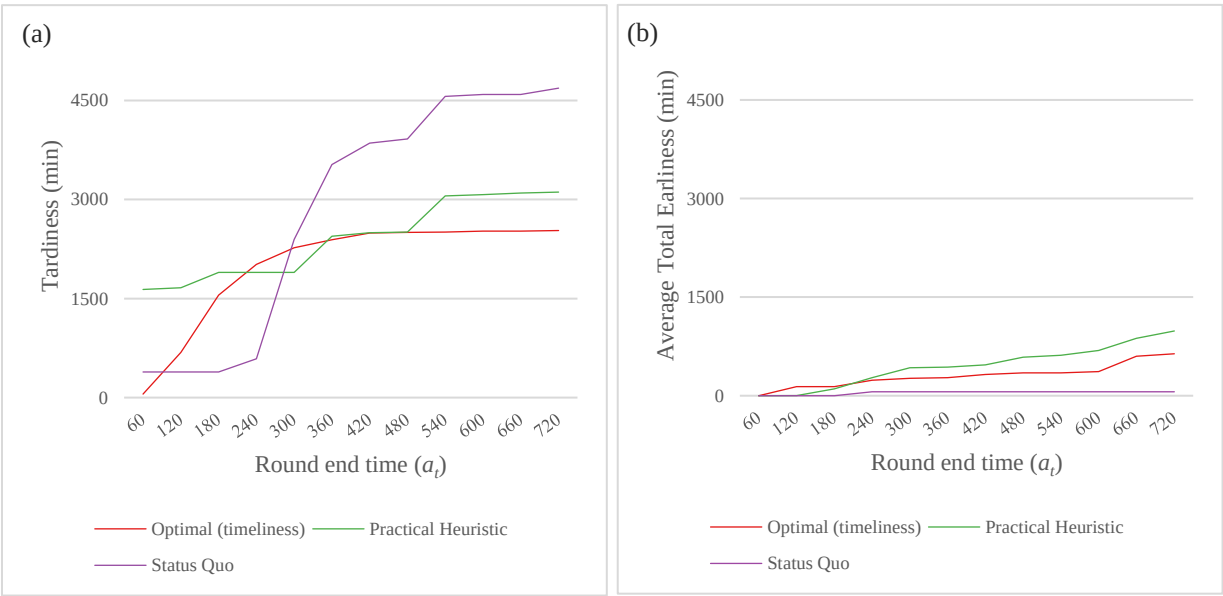

Figure 4.4: (a) Cumulative average tardiness, S3. (b) Cumulative average earliness, S3.

The analysis of the cumulative tardiness during the shift indicated that for more than half of the scenarios (56%) the practical heuristic had a smaller increment of tardiness over time than the status quo approach. In other words, even though the practical heuristic initiated the shift with more tardiness than the other approaches, the rate of increment was smaller than the status quo approach for about half of the scenarios. For instance, as shown in Figure 4.4.a the cumulative average tardiness for scenario S3 over time where the practical heuristic's curve had a smaller

slope than the status quo approach's curve. As a result, the status quo approach surpassed the tardiness of the practical heuristic at the end of the shift.

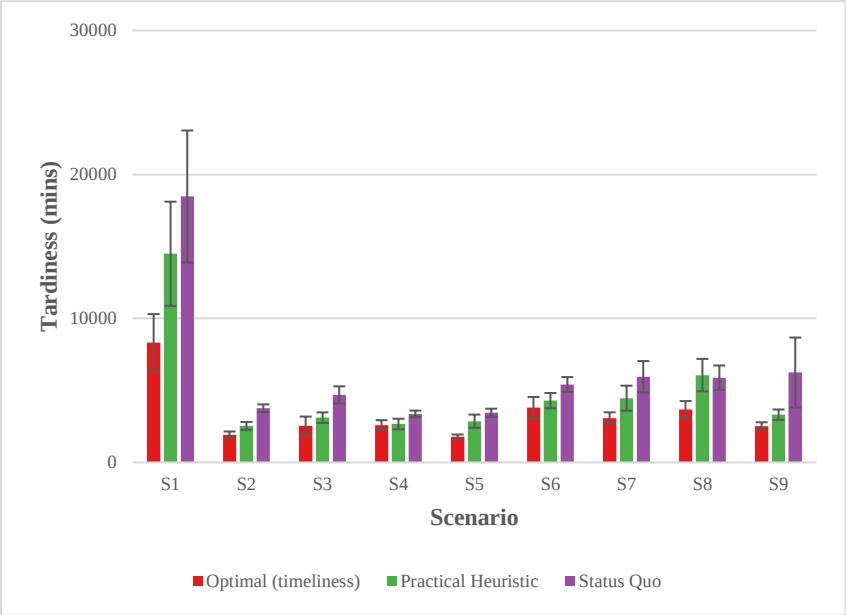

Figure 4.5: Average tardiness per shift.

The trade-off between tardiness and distance walked observed in the results was expected because of the relationship between the timeliness and spatial dispersion measures observed in the optimal solutions studied in Chapter 3. Moreover, the practical heuristic had tardiness and distance walked results similar to the optimal-timeliness and status quo approaches (see Figure 4.6). On the other hand, the practical heuristic had tardiness and distance walked results less similar to the optimal-spatial dispersion approach, as expected. For instance, the practical heuristic had tardiness values between 3,531.8 and 14,899.5 minutes while the optimal-spatial dispersion approach had tardiness values between 32,815.2 and 49,086.7 minutes. These results were expected because the practical heuristic considered timeliness as the primary objective in its design, relegating spatial dispersion (surrogate variable of distance walked) as a secondary and non-obligatory objective. Also, this

result could be considered as an advantage of the practical heuristic because it resembles the current practice more closely.

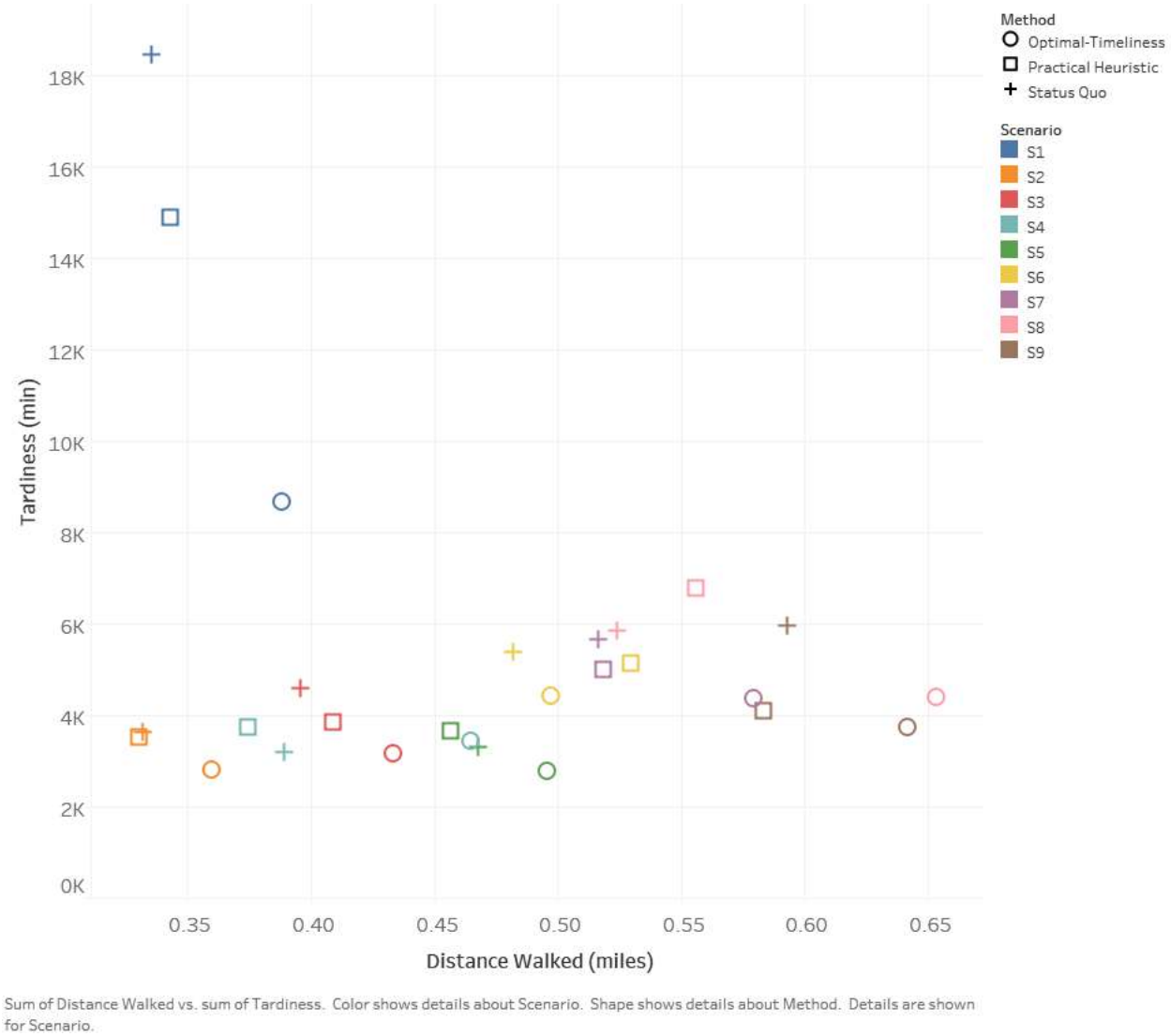

Figure 4.6. Scatterplot of the average tardiness and distance walked.

The practical heuristic and the status quo approach had on average negative actual slack time in the first round (round 1) for all scenarios, which implied that the PCA needed more time than the available time of the round 1 to finish the tasks assigned according to the work plan (see Figure 4.7.a). On the other hand, the optimal-timeliness approach had positive actual slack for the majority of the scenarios in the first round, which implied that the PCA finished the tasks assigned

to round 1 before the end of the round. Considering the actual slack of the optimal-timeliness approach as a baseline, the actual slack time of the practical heuristic was greater in absolute value compared to the actual slack time of the status quo approach for the majority of the scenarios in the first round. In contrast, at the end of the shift (round 12) the practical heuristic and the optimal-spatial dispersion approach resulted in positive actual slack time for the majority of the scenarios (88% of the scenarios in both cases). However, the optimal-timeliness and the status quo approaches had less positive actual slack at the end of the shift compared to the practical heuristic (55% and 22% of the scenarios, respectively) (see Figure 4.7.b).

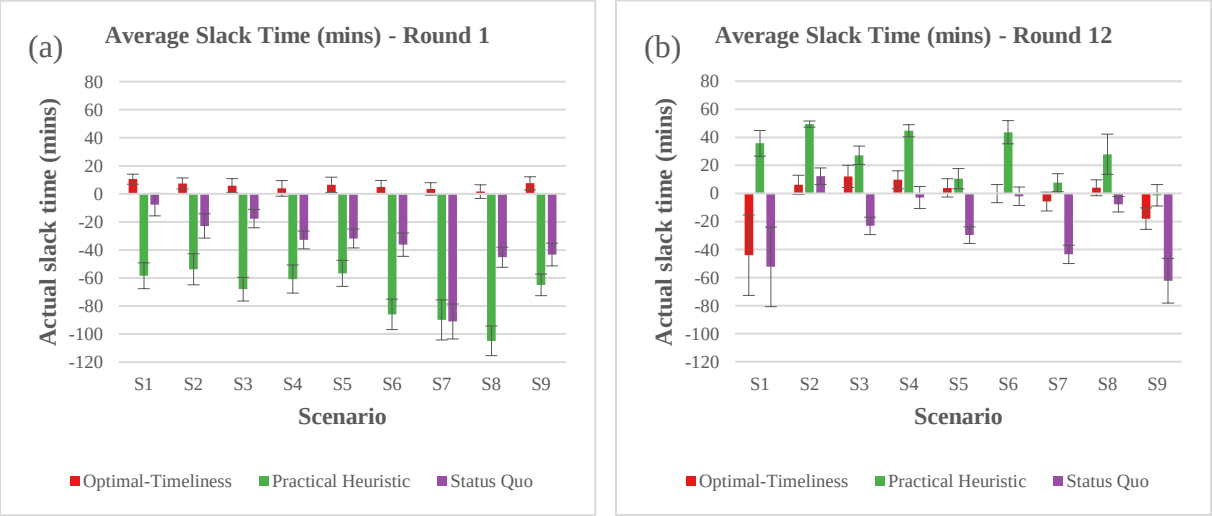

Figure 4.7: Average Actual Slack Time for scenario S3, (a) round 1 and (b) round 12.

Even though the practical heuristic initiated with more negative actual slack time than the status quo approach for all the scenarios, throughout the rest of the shift it accumulated less negative slack time and more positive slack time than the status quo approach. Because of this characteristic, at the end of shift the practical heuristic approach almost reached the same amount of accumulated actual slack time as the status quo or the optimal-timeliness approaches (see Figure 4.8). Further, considering all scenarios in the analysis, the results indicated that the practical heuristic had more rounds with positive actual slack than the status quo approach (practical heuristic: 71% of the

rounds, and status quo approach: 65% of the rounds) (see Figure 4.9 for some scenarios; see Figure B.1. for the rest of the scenarios). For instance, the results for scenario S4 indicated that the practical heuristic approach had more rounds with positive slack time than the status quo approach (practical heuristic: 6 rounds, and status quo approach: 4 rounds) (see Figure 4.10).

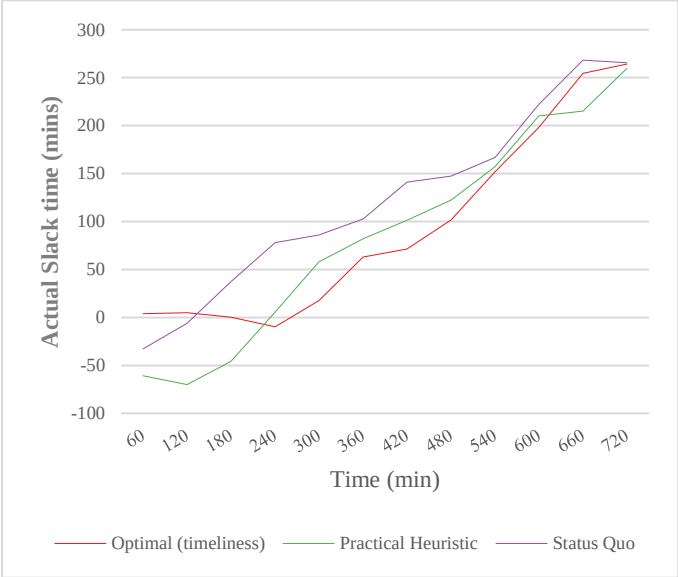

Figure 4.8: Average actual slack time, scenario S4.

In terms of the planned slack time (slack time considering only the tasks to be performed in the round according to the work plan), the status quo approach and the practical heuristic used more than the allowance considered in the optimization (10 minutes), as expected. Considering all scenarios analyzed, the practical heuristic had less negative slack time over time compared to the status quo approach (see Figure 4.11.a). The practical heuristic started with more negative slack time than the other approaches, but it reached approximately the same level of positive cumulative planned slack time at the end of the shift. As one example, the analysis of the cumulative planned slack time for scenario S3 showed that the slope of the practical heuristic's curve was smaller in value than the other approaches (see Figure 4.11.b).

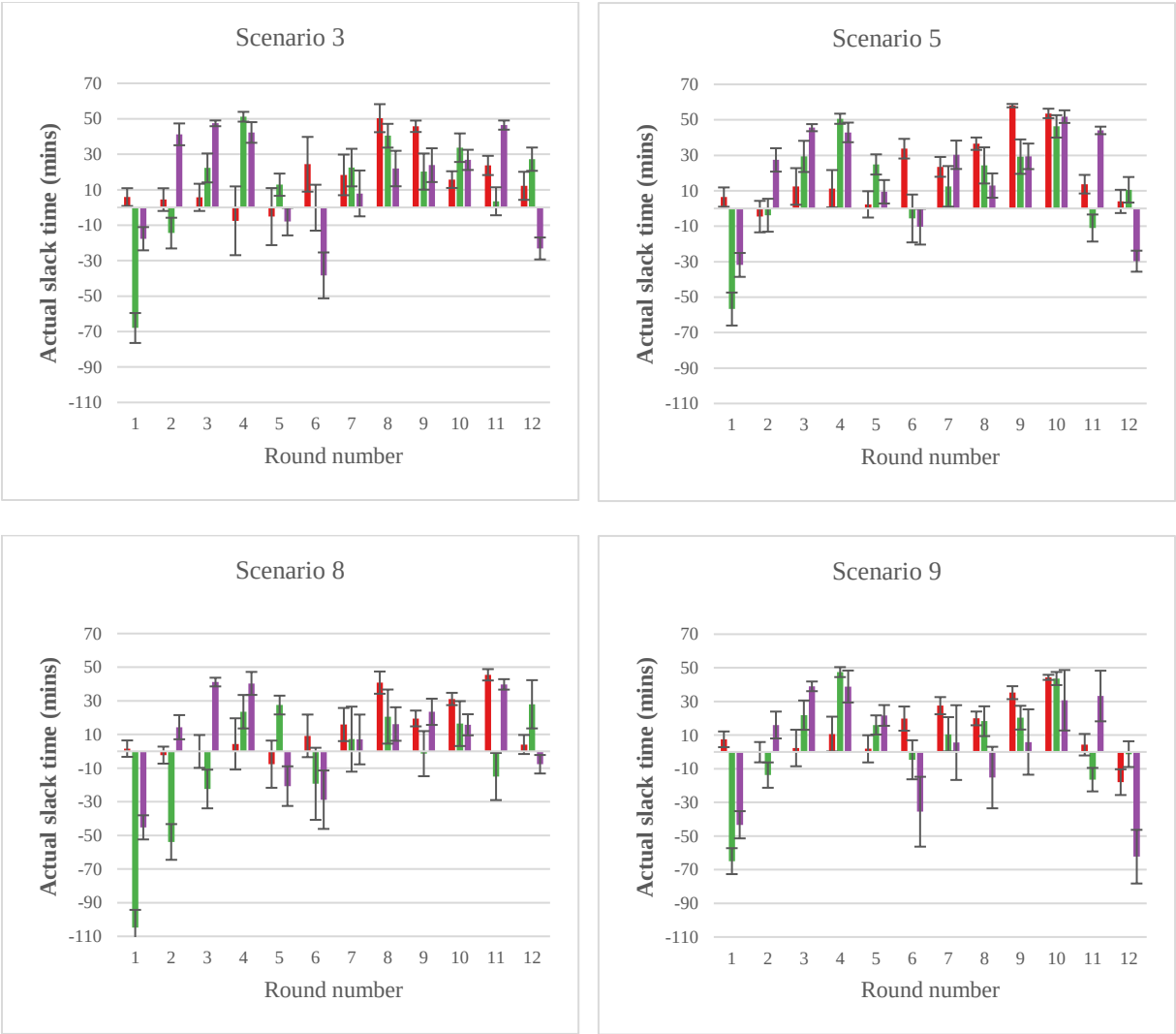

Figure 4.9: Average actual slack time, scenarios S3, S5, S8, and S9.

4.5. Discussion

A methodology is proposed to develop unit-specific practical heuristics to solve the SICWP problem by generating practical context-based work planning strategies. The resulting strategies were intended to improve the quality of the provider's work (e.g., minimize tardiness and distance walked) while considering the provider's cognitive limitations. The methodology was exemplified with data from an inpatient healthcare unit. A workload assessment technique was used to determine the feasibility of implementing the practical heuristic while considering

limited computational resources similar to those currently in use. A Monte Carlo simulation was used to compare the performance of practical heuristics against the performance of the optimal approach and current strategies.

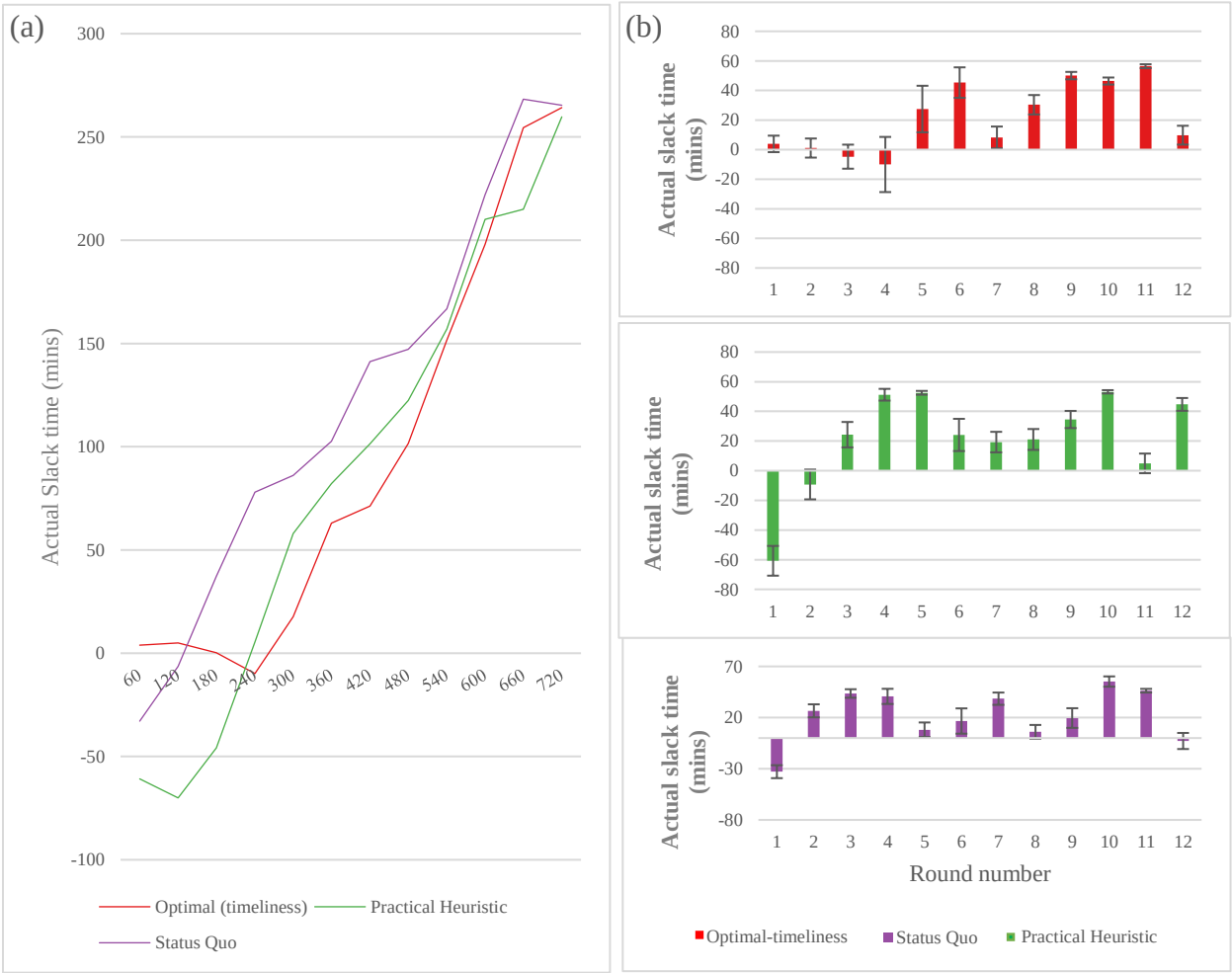

Figure 4.10: (a) Cumulative average actual slack time, scenario S4. (b) Average actual slack time, scenario S4.

The proposed methodology to develop unit-specific practical heuristics consists of five steps: unit-specific parameters estimation, baseline workload scenarios generation, solution of baseline scenarios to optimality, rule-based analysis of task-to-round assignment, and definition of unit-specific practical heuristic. Since these steps can be applied to most inpatient care units with a

SICWP problem, the proposed methodology may offer a general and practical procedure to improve the quality of the SICWP problem's solutions.

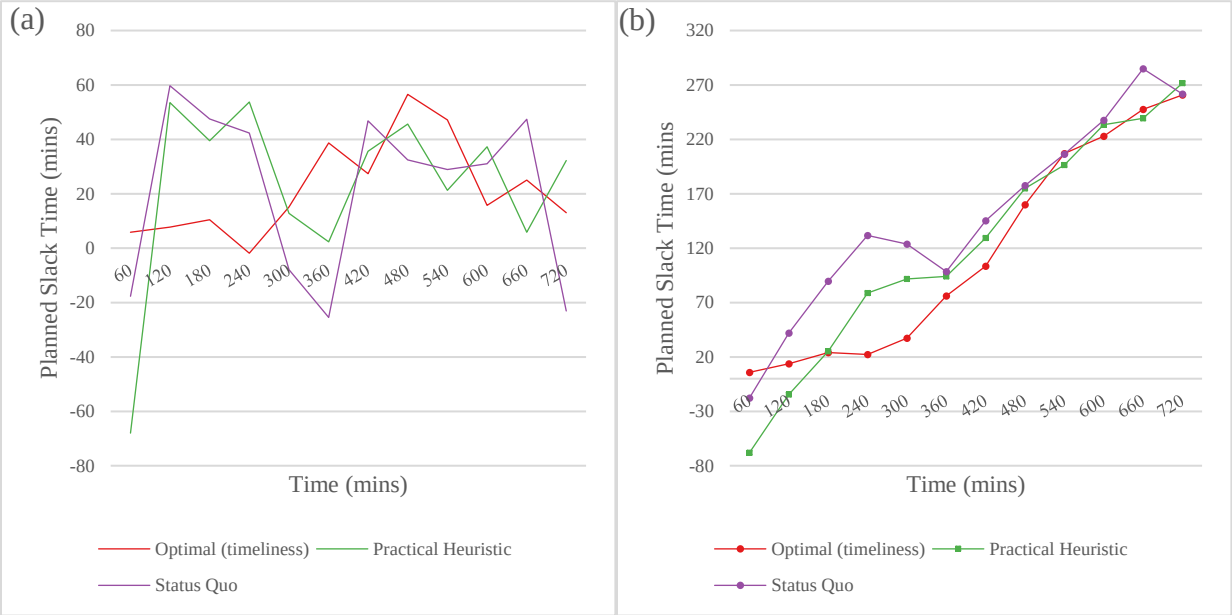

Figure 4.11: (a) Planned average slack time, S3. (b) Cumulative planned average Slack Time, S3

The cognitive workload of the practical heuristic for the specific unit was greater than the status quo approach but close enough to be potentially useful in practice without computational resources. Because the optimal approach required computational resources to be solved, it was used in this study as part of the off-line design of the practical heuristic to solve the baseline scenarios and as part of the performance evaluation to solve the test scenarios. In order to implement the optimal approach on a day-to-day operation, computational resources, such as memory space and bandwidth, plus the added workload of using such resources should be in the implementation plan.

Based on the simulation results, the practical heuristic for the specific unit was better than the status quo approach and worse than the optimal-timeliness approach in terms of tardiness for

most of the scenarios, as expected. In terms of the total distance walked, the healthcare provider will walk about the same distance regardless of the solution approach. Even though the practical heuristic presented improvement only in terms of the tardiness quality measure when compared against the status quo approach, it fulfilled the design's first-priority objective. Although these conclusions have been obtained for a particular inpatient care unit's data, the methodology can be replicated to analyze and design a practical heuristic approach that fits the characteristics of data from a different inpatient care unit.

Although the slack time was not part of the evaluation criteria when obtaining the optimal solutions but a constraint set instead, the simulation results were analyzed in terms of actual and planned slack time to identify characteristics of the workload in each round. Based on the simulation results the practical heuristic initiated the shift with more negative actual slack time than the other approaches in all scenarios. However, at the end of the shift the practical heuristic had more positive actual slack time than the other approaches in almost all scenarios. These results indicated that a delegation strategy may be needed to reduce the negative slack time during the first round when using the practical heuristic. On the other hand, a delegation or overtime strategies may be needed to reduce the negative slack time during the last round when using the optimal-timeliness or status quo approaches. The simulation results indicated positive values of planned slack time in all rounds for the optimal-timeliness approach, as expected. In sum, the performance comparison of the approaches in terms of actual slack time may provide insights about the need of additional strategies, such as delegation of tasks and overtime work, per round and type of approach.

For many inpatient healthcare facilities, the necessary resources to implement an optimal or close-to-optimal solution could be considered a barrier to putting them into practice, even in the

years to come. Nevertheless, the proposed methodology to develop practical strategies may provide a non-optimal but low-cost approach to improving the quality of the provider's work. Improving the quality of the assignment of the tasks in the shift may have other indirect benefits, such as reducing burnout of providers and improving patient care.

As we developed the simulation for this analysis, it was realized there are many decisions the worker needs to make as the day progresses, as processing times are realized, and as interruptions arise. Some of these decisions include sequencing and resequencing tasks within rounds and deciding what to do upon an interruption. Once a better understanding of these factors is acquired, a better simulation framework can be developed that can not only help evaluate work planning strategies, but also help develop work execution strategies, evaluate those strategies, and assess the capacity of inpatient care work systems.

4.6. References

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CHAPTER 5

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

5.1 Conclusions

Motivated by the burden of high healthcare costs and low quality of care, the need to improve the performance of healthcare systems has gained increasing attention in recent years [1, 5]. In response to the observed quality problem in healthcare, the Institute of Medicine (IOM) proposed six quality aims to guide the efforts to improve healthcare delivery as part of its vision of health systems in the 21st century. The IOM proposed that health care should be safe, effective, efficient, timely, equitable, and patient-centered [5]. Even though several years have passed since these recommendations were published, there has been limited progress towards an integrated improvement of the healthcare quality in all six dimensions [1]. Moreover, the evaluation of healthcare quality still focuses on one aim at a time. In this dissertation, the integration of the six IOM quality aims into operational decision-making was studied through the design and evaluation of solutions for two healthcare problems. The first part of the dissertation studied the integration of the IOM aims into the performance evaluation of trauma centers. The second part of the dissertation studied the integration of the IOM aims to solve SICWP problem in an optimal as well as practical manner. The conclusions and future research directions for the two parts of the dissertation are discussed separately in the following paragraphs.

The first part of this dissertation, presented in Chapter 2, evaluated two approaches to integrating the IOM aims into the performance evaluation of healthcare institutions. The results of these evaluations provided information about the challenges and opportunities related to the assessment of trauma care at the institutional level. Thus, this study provided insights to support decision-makers in selecting the appropriate approach to evaluate trauma centers' performance

while considering the IOM quality aims. Quality metrics for four of the six aims were identified from the literature and calculated using data from a particular healthcare system. There were significant challenges to integrating the equity and patient-centeredness aims because the dataset lacked the information necessary to calculate the quality indicators related to these aims at the hospital level. Although the implementation of the approaches included quality indicators based on the literature, decision-makers can replace them with more appropriate quality indicators for their institutions. Moreover, if quality indicators become available for the patient-centeredness aim, they can be included in the approaches because of the generalizability of the proposed methods.

This study first proposed a multi-criteria approach to integrating the IOM quality aims in the performance evaluation of trauma care based on deterministic dominance theory. The proposed approach differs from the traditional approach in the method used to determine the performance categories of trauma centers. Although this different method of performance categorization can be a challenge for practitioners, the approach overcomes the heterogeneity of quality metrics in evaluating trauma care performance, eliminating the need to modify validated quality metrics. Thus, this study contributed to the literature by proposing a new multi-dimensional perspective to evaluate quality at the institutional level. Nevertheless, another disadvantage of this approach was identified upon the failure of a modification, which attempted to increase the chances of acceptance by practitioners. In this modified approach, the method to determine the performance categories of trauma centers could not be used for some TCs when CIs were added into the analysis. In some cases, the method categorized the same TC as high and low performer simultaneously. Because of this, the study moved towards the traditional approach for a more detailed analysis of the integration of all the IOM quality aims into the performance evaluation of trauma centers.

This study also proposed a second approach to integrate the IOM quality aims into a single overall composite score. In this traditional approach, a composite was constructed based on the Individual Hospital Weighted Average method and the Centers for Medicare & Medicaid Services Hospital Quality Incentive Demonstration method. This study contributed to the literature by proposing a method to integrate the equity aim into performance evaluation by adjusting a single overall composite score that could include all the other quality aims. The implementation of the two composite methods provided insights about the preprocessing needs for the quality metrics and the effect of the weights allocated to each aim in the resultant categorizations of the trauma centers. The results indicated that the weights of the aim in each method were affected not only by the structure of the composite but also by the data composition.

Regardless of the approach used, integrating the IOM quality aims into the performance evaluation of trauma care could fill the research gap in the literature. The proposed multi-aim composite methods could be adapted to evaluate institutional performance in healthcare settings other than trauma care. Data collection platforms such as trauma registries need to be designed to ensure availability of metrics for all IOM quality aims. To guarantee continuity in performance evaluations, trauma registries need to become flexible enough to assimilate changes in quality indicators per aim.

The second part of this dissertation includes two chapters. In chapter 3, the study investigates practical strategies for the SICWP problem considering the IOM quality aims. This study contributed to the literature by proposing an optimization model based on the 0–1 generalized assignment problem with nonlinear capacity constraints. For the evaluation criteria, the study proposed metrics consistent with the IOM quality aims. These evaluation criteria included metrics for the efficiency, timeliness, and safety aims; the equity and patient-centeredness

aims were included indirectly. However, the effectiveness aim was considered out of the scope of the problem. This study also could help decision-makers gain insight into the complexity of the SICWP problem when solved to optimality. The study also exposed the challenges of integrating IOM quality aims into the problem formulation. Based on the characterization of the problem and the analysis of the optimal solutions, the study proposed a research agenda to support decision-makers in the analysis of the SICWP problem. Our literature review identified a research gap in using OR techniques to analyze or improve inpatient care work planning decisions. The proposed model fills the research gap to support the healthcare provider by identifying optimal strategies for the SICWP problem. Besides, the proposed optimization model incorporated metrics representing some of the IOM quality aims into the evaluation criteria and, as a result, into the optimal solutions for the SICWP problem. Thus, the proposed optimization model is aligned with the recommendation that healthcare improvement efforts should be guided by the IOM quality aims. Future directions of this study include the implementation of the identified research opportunities to support the healthcare provider's decision-making process while considering the IOM quality aims. These research opportunities include (1) the development of graphical tools to support work analysis, planning, and execution, (2) the definition and analysis of unit-specific parameters and performance metrics consistent with quality goals, (3) the analysis of work planning decisions under uncertainty, (4) the design and development of work execution strategies.

In chapter 4, the study proposed a methodology to develop unit-specific practical heuristics to solve the SICWP problem while considering the IOM quality aims. The proposed methodology included the analysis of optimal solutions obtained using the formulation and objective criteria proposed in Chapter 3. The objective criteria included metrics related to the timeliness and efficiency aims. The other quality aims were either correlated or indirectly related to these aims.

The proposed methodology included the evaluation of the unit-specific work planning heuristic in terms of cognitive complexity and performance. This study contributed to the literature by proposing a methodology to develop unit-specific practical heuristics that solves the SICWP problem and evaluates the effects on the provider in terms of the cognitive complexity and performance. The evaluation of the cognitive complexity for the case study confirmed that the healthcare provider could use the heuristic without additional computational resources. The evaluation of the heuristic's performance for the case study indicated that there was some degree of improvement in relation to the performance of the current approach. Since the motivation of this study was found among the research agenda developed in the previous chapter, the research gap not only consists of the utilization of OR in the analysis or improvement of the SICWP problem, but also consists of the development of a practical solution approach for the SICWP problem. Additionally, this practical solution approach is intended to be solved by the provider without the need of sophisticated computing equipment. Thus, the proposed heuristic fills the research gap in the literature by proposing a methodology to develop unit-specific practical heuristics that could provide better-than-current strategies to solve the SICWP problem while maintaining minimal computational resources. Moreover, the proposed approach aligns with the IOM recommendation by integrating the six quality aims into the design and evaluation of practical strategies to solve the SICWP problem. Furthermore, the proposed methodology could be extended to develop practical heuristics for healthcare settings with similar characteristics to the SICWP problem setting.

In sum, the integration of the IOM quality aims into operational decision-making was achieved through the design and evaluation of solutions for two different healthcare problems. The principal outcomes were insights about challenges observed in the design and implementation of

the solutions, along with the methodologies developed in each study. The difficulties and challenges experienced while integrating the IOM quality aims into the problems' solutions need to be addressed urgently by researchers and decision-makers. The slow progress towards integrating the six IOM aims into operational decision-making in the studied settings may change positively with the reduction of the difficulties and challenges.

5.2 Future Research Work

In recent years, the need to improve the quality of care has been recognized as critical for improving health in developing countries [42]. The study in Chapter 2 could be extended by integrating the IOM quality aims into the performance evaluation of healthcare settings (e.g., pediatric care, hospital) at institutional level in developing countries. As a result, further research will focus on investigating methods, e.g., sampling, in order to overcome important challenges that usually characterize developing countries, such as limited availability of patient registries, limited quality of data, and limited budgets.

Furthermore, these limitations in data collection could introduce additional uncertainty in constructing the composite, besides the most common sources of uncertainty, such as data normalization and imputation [43]. In this scenario, it would become more imperative to evaluate the robustness of the proposed methods. For future work, uncertainty and sensitivity analysis will be investigated and incorporated into the design of the composite.

Some healthcare settings with similar dynamics to the SICWP problem may have enough resources to link a portable electronic device to the patient's electronic medical records that could report the ideal work plan using an optimization model. Moreover, this device could update the ideal work plan report to the provider every time a change in the system occurred (e.g., variations in the set of tasks, time when a task is completed). Thus, the provider would no longer need to

spend time and mental effort solving the initial work plan or updating it throughout the shift. Since the ideal work plan would guide the provider through the shift to execute the tasks, the need for rounds is eliminated. Thus, as one of the future work directions, the model to solve SICWP problem without rounds will be investigated. In addition, both models could be compared in terms of their quality after execution to identify possible improvements.

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APPENDIXES

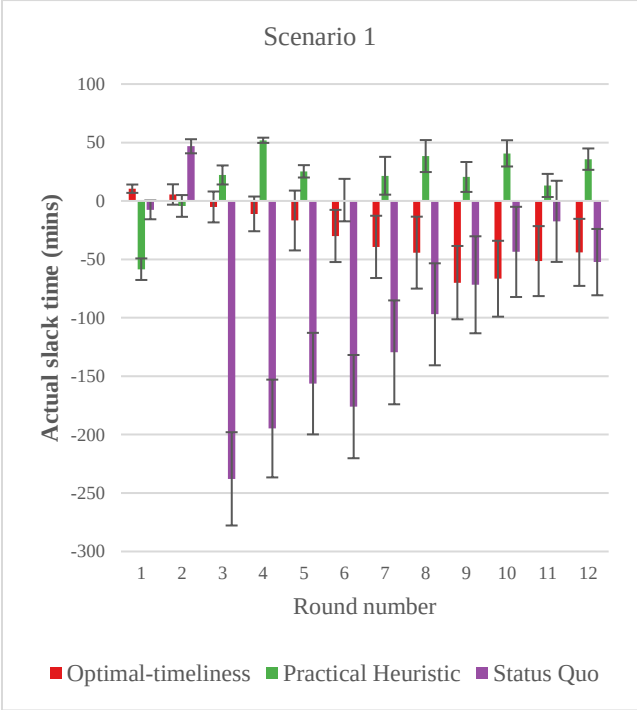
APPENDIX A

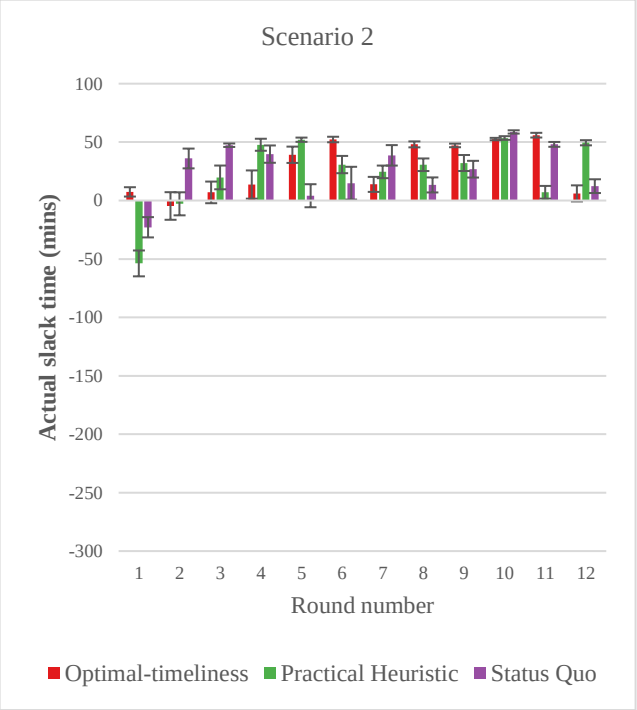
TABLE A.1.

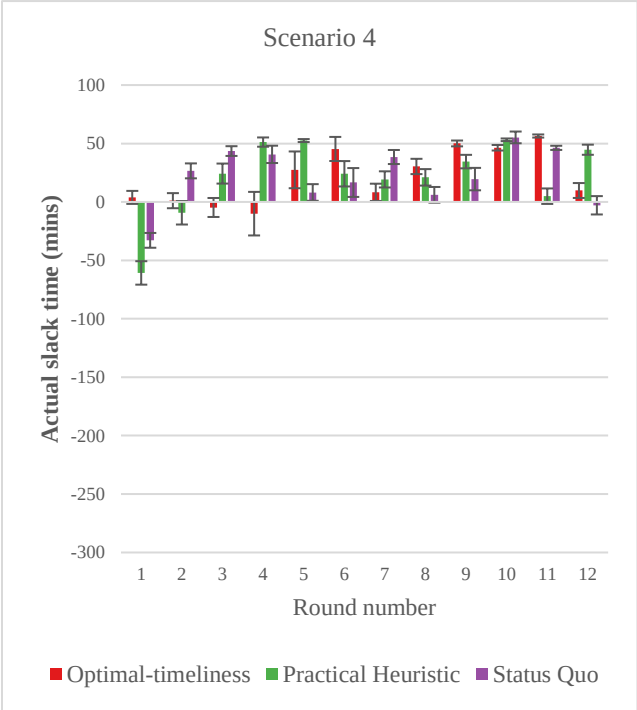
BASELINE SCENARIOS CHARACTERISTICS

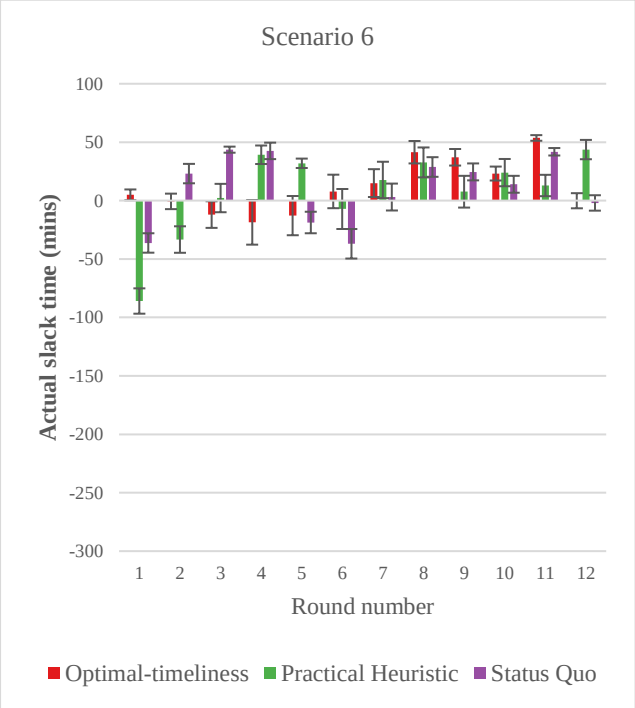
Scenario	Total patients	Patients with Vitals Q6	Patients with Vitals Q4	Patients with NPO (Y = 1)	Patients with ACHS (Y = 1)	Independent Patients	Non-Independent Patients	Patients with Bedrest	Patients with Incision Care
1	7	4	3	3	1	2	5	2	0
2	7	7	0	1	1	7	0	0	3
3	7	3	4	1	3	2	5	2	4
4	7	2	5	3	3	2	5	3	5
5	7	1	6	3	3	0	7	3	7
6	7	6	1	1	1	6	1	1	1
7	7	7	0	0	0	0	7	2	0
8	4	1	3	3	1	0	4	1	0
9	5	2	3	3	1	0	5	2	0
10	6	3	3	3	1	1	5	2	0
11	4	4	0	1	1	4	0	0	3
12	5	5	0	1	1	5	0	0	3
13	6	6	0	1	1	6	0	0	3
14	4	0	4	1	3	0	4	2	4
15	5	1	4	1	3	0	5	2	4
16	6	2	4	1	3	1	5	2	4
17	4	0	4	3	3	0	4	3	4
18	5	0	5	3	3	0	5	3	5
19	6	1	5	3	3	1	5	3	5
20	4	0	4	3	3	0	4	3	4
21	5	0	5	3	3	0	5	3	5

APPENDIX B


Scenario 1
Actual slack time (mins)
100
50
0
-50
-100
-150
-200
-250
-300
1 2 3 4 5 6 7 8 9 10 11 12
Round number
Optimal-timeliness
Practical Heuristic
Status Quo


Scenario 2
Actual slack time (mins)
100
50
0
-50
-100
-150
-200
-250
-300
1 2 3 4 5 6 7 8 9 10 11 12
Round number
Optimal-timeliness
Practical Heuristic
Status Quo


Scenario 4
Actual slack time (mins)
100
50
0
-50
-100
-150
-200
-250
-300
1 2 3 4 5 6 7 8 9 10 11 12
Round number
Optimal-timeliness
Practical Heuristic
Status Quo


Scenario 6
Actual slack time (mins)
100
50
0
-50
-100
-150
-200
-250
-300
1 2 3 4 5 6 7 8 9 10 11 12
Round number
Optimal-timeliness
Practical Heuristic
Status Quo

APPENDIX B (continued)

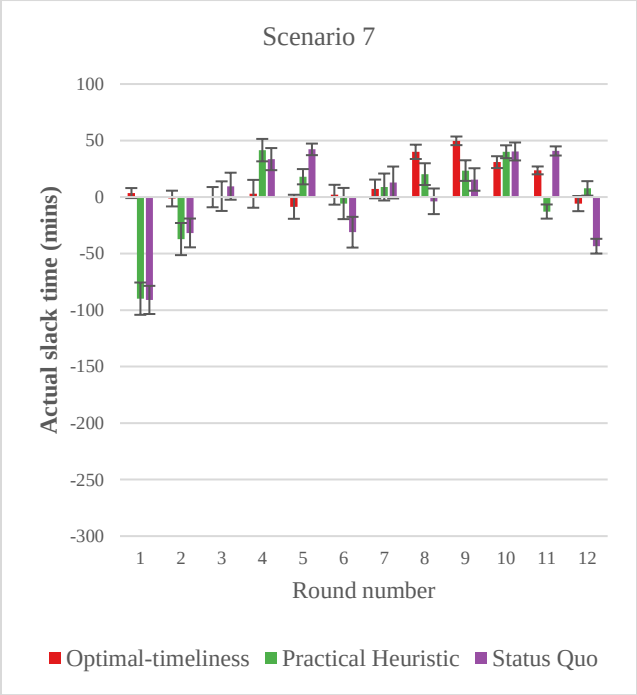


Figure B.1: Average Actual Slack Time for scenarios S1, S2, S4, S6, and S7.