Anesthesiologist Scheduling with Handoffs: A Combined Approach of Optimization and Human Factors

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Abstract

We present a two-stage stochastic programming model for optimizing anesthesiologist schedules, explicitly accounting for uncertainty in surgery durations and anesthesiologist handoffs. To inform model design, we conducted an online survey at our partner institution to identify key factors affecting the quality of intraoperative anesthesiologist handoffs. Insights from the survey results are incorporated into the model, which optimizes the trade-offs between delaying anesthesiologist relief times, handoff costs, and under-staffing costs. To overcome the computational limitations of solving the extensive form of the proposed two-stage stochastic programming model, we develop a monolithic reformulation. Our computational experiments, based on real-world data from our partner institution, demonstrate that the reformulated model outperforms the extensive form in both computational times and optimality gap. Comparing our model's outputs with current staffing practice at the partner institution shows that the proposed approach achieves substantial cost reductions. Finally, sensitivity analyses highlight the model's ability to provide insights into trade-offs between handoffs, staffing levels, and relief times.

Keywords: Anesthesiologist scheduling, Handoffs, Provider Survey, Two-Stage Stochastic Integer Program

Highlights

- We address the problem of scheduling anesthesiologists in operating rooms under uncertainty in surgery durations and anesthesiologist handoffs.
- Key factors influencing the quality of intraoperative anesthesiologist handoffs are identified.
- We evaluate the trade-offs between anesthesiologist relief delays, handoff costs, and under-staffing costs.
- The proposed approach provides decision support for efficient and cost-effective anesthesiologist scheduling.
- Our findings can guide policies aimed at improving the quality of intraoperative handoffs.

1 Introduction

Care transitions – the transfer of information, authority, and responsibility for patient care between one or more clinicians [1], including handoffs or handovers – are critical to ensure safe, high-quality care [2]. Handoffs, the communication activity between clinicians, involve some risks due to potential loss or inaccurate transmission of information between providers, and ambiguity in authority and responsibility for patient care [3, 4]. However, they can also enhance patient safety, with opportunities for error detection, reassessing care decisions, and reviewing care with the input of another perspective [5, 6].

Despite the plethora of studies that characterize and recommend methods to improve handoffs in hospital settings [7–9], opportunities for improvement remain universally, but especially during the perioperative period, that is, immediately before, during and after surgery. Surgical care accounts for an estimated 50% of hospital expenditures and 30% of total healthcare costs in the U.S. [10]. Perioperative handoffs occur as the patient transitions from the preoperative to the intraoperative and postoperative phases of surgical care; handoffs also occur every time health care providers change shifts and take breaks [7, 11]. Errors and omission of information during perioperative handoffs can lead to complications that may require additional interventions such as infection or excessive bleeding, unanticipated disposition such as intensive care unit admission or extended length of stay, or post-procedural care such as readmission or rehabilitation [12]. A significant portion of perioperative handoffs are intraoperative [13]. These handoffs are mainly due to shift changes or breaks. Epstein et al. [14] and Hyder et al. [15] showed that intraoperative handoffs are high-risk and error-prone, often linked with inadequate verbal communication and documentation. Furthermore, Saager et al. [16] and Jones et al. [17] showed that intraoperative handoffs are associated with adverse patient outcomes. In this study, we focus on intraoperative anesthesia handoffs, as approximately 20% of patients undergoing surgery have anesthesia handoffs [18].

We first analyze if there are opportunities to improve intraoperative anesthesia handoffs at an academic healthcare center in the Eastern United States through an anonymous online survey; we investigate perceptions around teamwork, staffing, and work pace-related factors in addition to the quality of intraoperative handoffs to provide insight into improvement strategies. We include teamwork because good communication between clinicians is part of good teamwork; if teamwork is poor, handoff communication may also be hindered and improvements may need to focus on changing culture within the organization. Staffing and work pace may also impact handoff quality because important patient care information can be lost during handoffs if providers work for long hours or rush because staffing levels are not adequate to handle the workload; in this case, improved staffing practices would be necessary to improve handoff safety and quality. The survey results indicate that there is room for improvement in the staffing levels and the quality of information exchange during handoffs. Hence, the main objective of this paper involves developing optimal schedules for anesthesiologists that balance staffing costs and handoffs under uncertain surgery durations. In particular, we focus on handoffs between anesthesiologists involving the transfer of responsibility for an operating room (OR). In our collaborating anesthesiology department, these handoffs occur because the daily schedules of anesthesiologists end based on a relief order. Hence, the frequency of handoffs can be reduced through careful planning of anesthesiologist schedules. To achieve this, we propose a stochastic programming model that considers the uncertainty in surgery durations. Overall, this study demonstrates an effective integration of human factors engineering and operations research in advancing healthcare delivery.

We use boldface lowercase letters to denote vectors and boldface uppercase letters to represent matrices. The remaining part of this paper is organized as follows. Section 2 presents the literature review. Section 3 summarizes the survey results, and Section 4 introduces the scheduling model. Section 5 presents computational experiments and managerial insights. Section 6 provides a discussion on the proposed modeling framework and concludes the paper.

2 Literature Review

Intraoperative handoffs are prone to communication errors due to the complexity of ongoing medical procedures and the need for precise, context-specific information. As a result, improving the quality and consistency of information transfer during intraoperative handoffs has emerged as a key target in patient safety initiatives and quality improvement programs [1]. Survey-based studies have been instrumental in quantifying perceptions of handoff quality, identifying contributing organizational factors, and evaluating interventions [19]. For instance, instruments, such as the Agency for Healthcare Research and Quality (AHRQ) Hospital Survey on Patient Safety Culture [20], have been adapted to capture clinicians' perspectives on information accuracy, timeliness, and completeness during handoffs and care transitions. As a solution to communication problems, interventions designed to improve handoffs typically involve redesigning care processes with stakeholder participation and team-based approaches [21]; developing checklists and mnemonics to support information transfer [22–24], implementing software tools to enhance communication and/or documentation [25, 26]. In this study, we also apply a survey to understand teamwork, staffing, and work pace-related factors influencing the quality of intraoperative anesthesia handoffs at an academic healthcare center in the Eastern United States. The interventions proposed in the literature can be implemented in our setting to enhance the quality of information exchange during intraoperative handoffs. None of the previous handoff studies, however, offered a more comprehensive solution that would also eliminate unnecessary handoffs. In this paper, we take a step forward and optimize the schedules of anesthesiologists to reduce the number of handoffs.

The literature on provider scheduling in ORs can generally be divided into two main categories. The first focuses on integrating provider scheduling with surgery scheduling [27–31], while the second focuses on scheduling providers based on a pre-determined surgery schedule [32–35]. Among these, some studies incorporate uncertainty in surgery durations [27, 29, 34] whereas others solve a deterministic problem. Rath et al. [36] and Tsang et al. [37] develop integrated models that address both surgery and anesthesiologist scheduling under uncertain surgery durations. However, these papers do not consider handoffs between providers and those that consider uncertainty in surgery durations allow providers to work overtime to mitigate the impact of uncertainty. We focus on the allocation of anesthesiologists to ORs for a given surgery-to-OR allocations and surgery start times. We account for uncertainty in surgery durations and model handoff of ORs between anesthesiologists.

There exist few papers that consider handoffs in healthcare scheduling and resource allocation. Kazemian et al. [38] propose an integer programming model to create shift schedules for medical trainees with the aim of reducing patient handoffs. Similarly, Smalley et al. [39] develop a mixed-integer programming approach for physician scheduling that reduces patient transfers among physicians. However, both studies are limited to deterministic, non-surgical settings. Sun et al. [40] addresses anesthesiologist scheduling at a tactical level over a multi-week planning horizon. Their model is focused on designing shifts and allocating providers to those shifts. Although handoffs are allowed in their framework, their impact on quality of care is not considered. In contrast, we address anesthesiologist scheduling at the operational level with a focus on reducing handoffs under uncertain surgery durations. Sinha et al. [41] proposed two-stage stochastic model for assigning certified registered nurse anesthetists (CRNAs) to ORs while reducing handoffs. However, there exists operational differences between CRNA and anesthesiologist scheduling at our partner institution. CRNA scheduling involves assigning nurses to shifts, with each nurse dedicated to a single OR. In contrast, anesthesiologist scheduling involves determining each anesthesiologist's relief time. Additionally, each anesthesiologist can be assigned to multiple ORs in one time-period.

Key contributions of this paper are stated below:

- We investigate the factors that affect the quality of intraoperative anesthesia handoffs through an online survey conducted at our partner institution, a tertiary hospital in the Eastern United States. Insights from this survey inform the design of our scheduling model.
- We present a two-stage stochastic program (2SSP) for scheduling anesthesiologists under surgery duration uncertainty. The proposed model captures the trade-offs between delaying the relief of anesthesiologists and the costs incurred due to handoffs and under-staffing.
- To address computational challenges associated with solving the extensive form of 2SSP, we introduce an alternative monolithic integer programming reformulation. Our computational experiments demonstrate that this reformulation achieves lower optimality gaps with reduced computational times compared to the extensive form.
- We apply our model to historical data from our partner institution and compare its outcomes with the institution's existing staffing practices. Our analysis reveals that the proposed framework achieves substantial cost savings over the current practice.

3 Quality and Safety of Intraoperative Anesthesia Handoffs

We designed a survey to examine the relationship between quality and safety perceptions of intraoperative anesthesia handoffs and factors such as teamwork, staffing levels and work pace. The survey was administered to anesthesia providers, including attending physicians, residents, and anesthetists at an academic medical center in the Eastern United States. It was conducted online using Qualtrics. We announced the survey through meetings, emails to department listservs, and flyers with a brief explanation of the study goal and the survey link. We began recruitment in March 2024 and closed the survey in June 2024. Participation in the study was voluntary and anonymous, and participants could withdraw at any time.

The survey included questions about the role and demographics of participants, composite measures from the Agency for Healthcare Research and Quality (AHRQ) Survey on Patient Safety (SOPS) Hospital Survey 2.0 [20], descriptions of the current intraoperative handoff process in general and the last handoff they participated in specifically, and finally improvement suggestions. Table 1, provides the definitions of the three AHRQ SOPS composite measures we included [20]. We included the handoff/information transfer composite measure for three kinds of handoffs: break/relief handoffs (temporary), handoffs to assume care (permanent) and shift change handoffs (permanent). Both positively worded items (e.g., "During busy times, staff in this unit help each other.") and negatively worded items (e.g., "Staff in this unit work longer hours than is best for patient care.") were included in all three measures.

Table 1: Definition of three composite measures adapted from AHRQ SOPS [20]

Composite measure	Definition
Teamwork	"Staff work together as an effective team, help each other during busy times, and are respectful."
Staffing and work pace	"There are enough staff to handle the workload, staff work appropriate hours and do not feel rushed, and there is appropriate reliance on temporary, float, or PRN staff."
Handoffs and information exchange	"Important patient care information is transferred across hospital units and during shift changes."

We analyze the results for three composite measures: teamwork, staffing and work pace, and handoffs and information exchange. Definitions of these measures are provided in Table 1. To calculate participants' opinions score on these measures based on the user guide [20], we retained the scores for positively worded items as they were (i.e., Strongly agree= 5, Agree= 4, Neither agree nor disagree= 3, Disagree= 2, Strongly disagree= 1), recoded the scores for negatively worded items (i.e., Strongly agree= 1, Agree= 2, Neither agree nor disagree= 3, Disagree= 4, Strongly disagree= 5). We then computed the score for each composite measure for each participant as the average across the included items. After computing the score for each composite measure by individual, we computed descriptive statistics and compared perception by role by conducting ANOVA in R; significant differences were investigated using a Tukey test.

A total of 60 participants (22 anesthesia attending physicians, 10 residents, and 28 anesthetists) started the survey, with 46 completing the entire survey. Some participants partially completed the survey and were included in related analyses. Table 2 shows the detailed demographic characteristics of the participants.

Table 2: Demographic Characteristics of Participants

Characteristics	n	%
Job Title		
Attending Physician	22	37
Resident	10	17
Anesthetist	28	43
Gender		
Male	22	37
Female	24	40
Missing	14	23
Race		
White	42	70
Asian	1	2
Prefer not to answer	3	5
Missing	14	23

Note: N=60

The average scores for teamwork, staffing and work pace, and handoffs and information exchange are shown in Table 3. Participants' opinions on teamwork (F (2,57) = 0.971, p = 0.385) and handoffs and information exchange (F (2,45) = 2.899, p = 0.066) did not vary significantly by role. However, opinions on staffing and work pace varied significantly based on role (F (2,57) = 3.510, p = 0.036). Tukey's HSD test revealed a significant difference between attending physicians and anesthetists (p = 0.041) with anesthetists expressing a more negative opinion of staffing and work pace (M = 2.91/5) compared to attending physicians (M = 3.41/5). No significant differences were found between residents and attending physicians (p = 0.973), or between residents and anesthetists (p = 0.215).

Table 3: Means, Standard Deviations, and One-Way Analyses of Variances in Three Composite Measures and Roles

Composite Measures	Mean (Standard Deviation)			F (p-value)
	Attending Physicians	Residents	Anesthetists	
Teamwork	4.32 (0.76)	4.23 (0.47)	4.08 (0.48)	0.971 (0.385)
Staffing and Work Pace	3.41 (0.78)	3.35 (0.57)	2.91 (0.68)	**3.510(0.036)***
Handoffs and Information Exchange	3.59 (0.77)	2.98 (0.69)	3.65 (0.74)	2.899 (0.066)

Note: * Indicates significant difference ($p \leq 0.05$) between attending physicians and anesthetists' opinions on staffing and work pace.

Although the teamwork measure consistently received scores above 4, the perceptions of anesthesiology providers reveal opportunities for improvement in both staffing levels and the quality of information exchange during handoffs. These two factors are closely interrelated: when providers are overextended due to inadequate staffing or must rush to complete tasks, critical patient care information may be omitted and the opportunity to ask questions and engage in dialog may not exist during handoffs, which compromise the safety of the patient. Motivated by these survey findings, we aim to optimize anesthesiologist schedules to balance workload distribution and reduce the number of intraoperative handoffs, particularly under uncertainty in surgery durations. We consider the handoffs between attending anesthesiologists, which involve transferring responsibility for an OR. Handoffs involving CRNAs also occur and are specifically addressed in [41]. In our partner anesthesiology department, these transitions typically occur at the end of a provider's work-day, following a predetermined relief order. That is, anesthesiologists handoff the operating rooms they attend to other available anesthesiologists to end their daily schedules according to a relief order. As such, the frequency of handoffs can be effectively reduced through strategic schedule planning and optimization.

4 Model Formulation

We formulate a 2SSP for scheduling anesthesiologists to ORs. The model captures the trade-offs between the relief of anesthesiologists, handoffs and under-staffing, while accounting for the uncertainty in surgery durations. Specifically, given the daily allocations of surgeries to ORs and their start times, the proposed 2SSP determines the relief time of the anesthesiologists, and assigns the anesthesiologists to ORs for the time periods before their relief times in the first stage. These decisions can be made ahead of the surgery day, as soon as the surgery schedule becomes available. In the second stage, the expected cost of handoffs and under-staffing are evaluated for different realizations of surgery durations. The model aims to minimize the combined cost of delaying the relief time of anesthesiologists along with the expected cost of handoffs and under-staffing. We refer to this problem as Stochastic Anesthesiologist Scheduling with Handoffs (SASH).

Let I be the set of available anesthesiologists, indexed, without the loss of generality, in the ascending order based on their priority for earlier relief times. J be the set of ORs and T be the set of time periods. Parameter k represents the maximum number of ORs an anesthesiologist can cover in a time period. Let c_t^r denote the cost of relieving an anesthesiologist at the end of period t, c^h represent the cost of a handoff and c^u indicate the per-period cost of anesthesiologist under-staffing in an OR. Uncertainty in surgery durations is captured by a finite set of scenarios Ω, and p_ω is the probability of scenario $\omega \in \Omega$. Let $\bar{t}_j(\omega)$ be the last time period of the last surgery in OR j under scenario ω.

The binary variable y_{ijt} takes the value 1 if anesthesiologist i is allocated to OR j in period t, and 0 otherwise and x_{it} is a binary variable that equals 1 if anesthesiologist i is relieved at the end of period t, and 0 otherwise. $w_{ijt}(\omega)$ is a binary variable equal to 1 if there is a handoff from anesthesiologist i in OR j at the end of period t under scenario ω, and 0 otherwise and $s_{jt}(\omega)$ is a binary variable equal to 1 if there is an anesthesiologist under-staffing in OR j in time period t under scenario ω, and 0 otherwise. We summarize these notations in Table 4.

Table 4: Description of Notations

Sets and Parameters	
I	set of anesthesiologists
J	set of `OR`s
T	set of time periods
k	maximum number of `OR`s an anesthesiologist can cover in a time period
Ω	set of all scenarios
c^r_t	cost of relieving an anesthesiologist at the end of period t
c^h	cost of a handoff
c^u	per-period cost of anesthesiologist under-staffing in an `OR`
$\bar{t}_j(\omega)$	last time period of the last surgery in `OR` j under scenario ω
Indices	
i	index of anesthesiologist, $i \in I$
j	index of `OR`, $j \in J$
t	index of time period, $t \in T$
ω	index of scenario, $\omega \in \Omega$
First-stage decision variables	
x_{it}	1 if anesthesiologist i is relieved at the end of period t, 0 otherwise
y_{ijt}	1 if anesthesiologist i is allocated to `OR` j in period t, 0 otherwise
Second-stage decision variables	
$w_{ijt}(\omega)$	1 if a handoff occurs from anesthesiologist i in `OR` j at the end of time period t under scenario ω, 0 otherwise
$s_{jt}(\omega)$	1 if there is anesthesiologist under-staffing in `OR` in time period t under scenario ω, 0 otherwise

We formulate the two-stage stochastic program for `SASH` as follows:

$$(\mathcal{F}_1) \quad \text{Min} \quad \sum_{i\in I}\sum_{t\in T} c^r_t x_{it} + \mathcal{Q}(\mathbf{x},\mathbf{y}) \tag{1a}$$

subject to :

$$\sum_{i\in I} y_{ijt} \leq 1 \qquad \forall j \in J, t \in T, \tag{1b}$$

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

$$x_{(i+1)t} \leq \sum_{\tau=1}^{t} x_{i\tau} \qquad \forall i \in I \setminus |I|, t \in T, \tag{1d}$$

$$\sum_{j\in J} y_{ijt} \leq k \qquad \forall i \in I, t \in T, \tag{1e}$$

$$y_{ijt} \leq 1 - \sum_{\tau=1}^{t-1} x_{i\tau} \qquad \forall i \in I, \forall j \in J, t \in T, \tag{1f}$$

$$\mathbf{x} \in \mathbb{B}^{|I|\times|T|}, \ \ \mathbf{y} \in \mathbb{B}^{|I|\times|J|\times|T|}. \tag{1g}$$

Constraint (1b) ensures that an `OR` is allocated at most one anesthesiologist in each time period while Constraint (1c) ensures that each anesthesiologist is relieved. Constraint (1d) ensures that anesthesiologists are relieved in the increasing order of their index. Constraint (1e) ensures that each anesthesiologist is assigned to at most k operating rooms in any given time period, while constraint (1f) ensures that no anesthesiologist is assigned to any surgery after they are relieved. The objective function (1a) minimizes the total cost of relieving the anesthesiologists along with the expected total cost of handoffs and under-staffing, $\mathcal{Q}(\mathbf{x},\mathbf{y}) := \mathbb{E}_\omega Q(\omega,\mathbf{x},\mathbf{y}) = \sum_{\omega\in\Omega} p_\omega Q(\omega,\mathbf{x},\mathbf{y})$, where

$$Q(\omega,\mathbf{x},\mathbf{y}) = \text{Min} \sum_{i\in I}\sum_{j\in J}\sum_{t=1}^{\bar{t}_j(\omega)-1} c^h w_{ijt}(\omega) + \sum_{j\in J}\sum_{t=1}^{\bar{t}_j(\omega)} c^u \left(1 - \sum_{i\in I} y_{ijt}\right) \tag{2a}$$

subject to:

$$w_{ijt}(\omega) \geq y_{ijt} - y_{ij(t+1)} \qquad \forall i \in I, j \in J, t \in \{1,\dots,\bar{t}_j(\omega)-1\}, \tag{2b}$$

$$\mathbf{w}(\omega) \in \mathbb{R}_+^{|I|\times\sum_{j\in J}(\bar{t}_j(\omega)-1)} \tag{2c}$$

In the second-stage problem $\mathcal{S}(\omega)$, constraints (2b) account for handoffs in `OR` j. The objective function (2a) minimizes the total costs associated with handoffs and understaffing. For every first-stage feasible decision $(\mathbf{x},\mathbf{y})$, $s_{jt}(\omega) = 1-\sum_{i\in I} y_{ijt}$ $\forall j \in J, t \in \{1,\dots,\bar{t}_j(\omega)\}$ and $w_{ijt}(\omega) = \max\{(y_{ijt} - y_{ij(t+1)}), 0\}$ $\forall i \in I, j \in J, t \in \{1,\dots,\bar{t}_j(\omega)-1\}$ is a feasible solution to $\mathcal{S}(\omega)$. Thus, $\mathcal{F}_1$ has relatively complete recourse. The extensive form of $\mathcal{F}_1$, which is referred to as $\mathcal{F}_{ext}$, is given by:

$$\text{Min} \sum_{i\in I}\sum_{t\in T} c_t^r x_{it} + \frac{1}{|\Omega|}\sum_{\omega\in\Omega}\left(\sum_{i\in I}\sum_{j\in J}\sum_{t=1}^{\bar{t}_j(\omega)-1} c^h w_{ijt}(\omega) + \sum_{j\in J}\sum_{t=1}^{\bar{t}_j(\omega)} c^u\left(1-\sum_{i\in I} y_{ijt}\right)\right)$$
$$\text{subject to} : (1b) - (1g),\ (2b) - (2c).$$

$\mathcal{F}_{ext}$ can be solved using off-the-shelf mixed-integer programming solvers. However, the second-stage variables $w_{ijt}(\omega)$ and constraints (2b)–(2c) are replicated for each scenario, leading to a large-scale integer program whose computational complexity grows significantly with the number of scenarios. To mitigate this issue, we introduce additional first-stage variables and constraints to model handoffs. Specifically, let $\eta_{ijt} \geq 0$ be a set of first-stage variables satisfying $\eta_{ijt} \geq y_{ijt} - y_{ij(t+1)}$ $\forall i \in I, j \in J, t \in T \setminus |T|$. Then, the second-stage problem $\mathcal{S}(\omega)$ can be reformulated as:

$$\text{Min} \sum_{i\in I}\sum_{j\in J}\sum_{t=1}^{\bar{t}_j(\omega)-1} c^h \eta_{ijt} + \sum_{j\in J}\sum_{t=1}^{\bar{t}_j(\omega)} c^u(1-\sum_{i\in I} y_{ijt}) \tag{3}$$

Using (3), we can write the extensive form of in $\mathcal{F}_1$ as:

$$(\mathcal{F}_2) \quad \text{Min} \quad \sum_{i\in I}\sum_{t\in T} c_t^r x_{it} + \frac{1}{|\Omega|}\sum_{\omega\in\Omega}\left(\sum_{i\in I}\sum_{j\in J}\sum_{t=1}^{\bar{t}_j(\omega)-1} c^h \eta_{ijt} + \sum_{j\in J}\sum_{t=1}^{\bar{t}_j(\omega)} c^u(1-\sum_{i\in I} y_{ijt})\right)$$

subject to : (1b) − (1g),

$$\eta_{ijt} \geq y_{ijt} - y_{ij(t+1)}, \ \eta_{ijt} \geq 0, \quad \forall i \in I, j \in J, t \in T \setminus |T|.$$

The second-stage variables $w_{ijt}(\omega)$ and constraints (2b)-(2c) are not used in $\mathcal{F}_2$, and thus they are not replicated for every scenario. $\mathcal{F}_2$ offers superior computational performance over $\mathcal{F}_{ext}$ as demonstrated in Section 5.1.

5 Numerical Experiments

Our computational experiments are based on data from our partner institution, a tertiary medical hospital in the Eastern United States. The dataset consists of 14,883 surgeries across 24 specialties, spanning a period of 353 working days. For each specialty, Table 5 provides the mean and standard deviation of the surgery durations, along with the percentage share of total surgeries for each specialty. We model the surgery duration for each specialty using a log-normal distribution with mean and standard deviation given in Table 5. Following the scheduling practices of our partner institution, we assume that anesthesiologists begin their workday at 7 a.m., and can simultaneously cover at most 3 `OR`s in each time period ($k = 3$). We consider a 14-hour planning horizon from 7 a.m. to 9 p.m., divided into $|T| = 56$ 15-minute time intervals.

Let c^r denote the per-period staffing cost of an anesthesiologist. We assume $c_t^r = tc^r$ and set $c^r = 1000$ in our experiments. Subsequently, we set handoff cost (c^h) and per-period anesthesiologist under-staffing cost (c^u) using the parameters $\zeta_h = \frac{c^h}{c^r}$ and $\xi_u = \frac{c^u}{c^r}$, respectively. We consider three each values of $\zeta_h = 5, 10, 15$ and $\xi_u = 5, 10, 15$. For scenario sets of size $|\Omega| = 500$ and 750, assuming uniform scenario probabilities, we conduct a full factorial experiment over all combinations of ζ_h and ξ_u, resulting in nine distinct cases per scenario set size. For each case, we generate three random problem instances. Each instance includes all surgeries scheduled on a day sampled from the 353 days in our dataset. We generate scenarios by sampling the surgery durations from specialty-specific log-normal distributions. All computations are performed using Python 3.9.13 and Gurobi 11.0.2 on a machine with an 8-core Intel Xeon 2.60GHz processor and 64GB of RAM.

5.1 Computational Performance

In this section, we compare the computational performance of the $\mathcal{F}_2$ and $\mathcal{F}_{ext}$ models. To generate larger and more computationally challenging problem instances, we construct two new surgery schedules, referred to as Schedules A and B, by combining surgeries from two different days in the dataset. Table A1 in Appendix A reports the number of surgeries, open `OR`s, and anesthesiologists in Schedules A and B. Further details about each scheduled surgery—including its specialty, planned start time, and the assigned `OR`—are provided in Tables A2–A3.

Table 5: Summary of 353-Day surgery data

Specialty	Duration average (min)	Duration standard deviation (min)	Case mix (%)
Ophthalmology	47	32	23.42
Urology	51	34	23.40
Orthopedics	98	51	14.59
Otolaryngology	109	77	13.05
Gynecology	87	53	5.22
Pediatric ENT	72	58	3.95
Pediatric Ophthalmology	65	25	3.82
Surgical Oncology	99	56	2.90
Plastics	88	58	1.84
Dentistry	131	39	1.77
Pain	61	35	1.53
Podiatry	104	69	1.48
General	67	39	1.16
Pediatric Urology	60	33	1.06
Gastroenterology	71	47	0.28
Pediatric Orthopedics	94	35	0.17
Neurology	44	8	0.14
Pediatric Neurology	42	25	0.07
Pediatric General	93	30	0.05
Oral Surgery	100	46	0.05
Gynecology Oncology	52	0	0.01
Interventional Radiology	52	4	0.01
Obstetrics	53	17	0.01
Pediatric Gastroenterology	50	1	0.01

For each combination of ζ_h and ξ_u, we generate three random instances for Schedule A and three for Schedule B, resulting in a total of six instances per case. Each instance is solved with a target optimality gap of 1% and a time limit of 3600 seconds. Tables 6 and 7 report the computational performance of $\mathcal{F}_2$ and $\mathcal{F}_{ext}$ for $|\Omega| = 500$ and $|\Omega| = 750$ scenarios, respectively. We evaluate performance based on average (maximum) optimality gaps and runtimes. As shown in Table 6, $\mathcal{F}_2$ consistently outperforms $\mathcal{F}_{ext}$ across all cases by achieving smaller optimality gaps and faster solution times. For example, in Case 5, $\mathcal{F}_2$ achieves an average optimality gap of 1.16% in 2972 seconds across 6 instances, whereas the average gap for $\mathcal{F}_{ext}$ is 23.28% at the end of the 3600 seconds time limit. This performance gap is even more pronounced for instances with $|\Omega| = 750$ scenarios, as illustrated in Table 7. These results demonstrate that $\mathcal{F}_2$ is significantly more efficient and scalable than the extensive form $\mathcal{F}_{ext}$ for solving large-scale instances of the anesthesiologist scheduling problem. The ability of $\mathcal{F}_2$ to achieve near-optimal solutions within reasonable computational time makes it well-suited for practical deployment, especially in settings where timely decision-making is critical.

5.2 Analysis of the Model Results

We first present a sensitivity analysis for the handoff (ζ_h) and understaffing cost parameters (ξ_u). Then, we evaluate the benefit of incorporating uncertainty in surgery

Table 6: Comparison of $\mathcal{F}_2$ and $\mathcal{F}_{ext}$ over average (max) optimality gap (%) and computational runtime (seconds) for $|\Omega| = 500$.

Case#	Case	$\mathcal{F}_2$		$\mathcal{F}_{ext}$	
	ζ_h — ξ_u	Opt-Gap (%)	Runtime (s)	Opt-Gap (%)	Runtime (s)
1	5—5	1.62 (3.18)	3433 (3601)	10.53 (11.00)	3602 (3603)
2	5—10	3.89 (7.83)	3539 (3601)	13.34 (16.41)	3602 (3604)
3	5—15	6.20 (10.24)	3601 (3602)	12.67 (17.97)	3601 (3602)
4	10—5	1.40 (3.41)	3394 (3601)	10.33 (11.27)	3601 (3601)
5	10—10	4.36 (7.22)	3467 (3601)	11.38 (12.72)	3602 (3604)
6	10—15	5.07 (8.06)	3601 (3602)	13.26 (18.72)	3601 (3602)
7	15—5	1.10 (1.90)	2961 (3601)	9.44 (12.30)	3601 (3601)
8	15—10	3.00 (8.46)	3253 (3602)	10.06 (12.38)	3601 (3602)
9	15—15	5.68 (7.98)	3601 (3602)	9.55 (10.60)	3601 (3601)

Table 7: Comparison of $\mathcal{F}_2$ and $\mathcal{F}_{ext}$ over average (max) optimality gap (%) and computational runtime (seconds) for $|\Omega| = 750$.

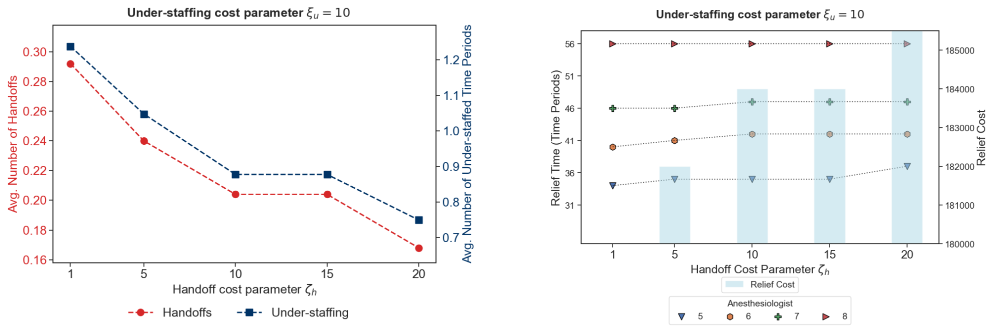
Case#	Case	$\mathcal{F}_2$		$\mathcal{F}_{ext}$	
	ζ_h — ξ_u	Opt-Gap (%)	Runtime (s)	Opt-Gap (%)	Runtime (s)
1	5—5	2.55 (4.92)	3331 (3602)	23.87 (48.76)	3601 (3602)
2	5—10	5.92 (8.39)	3601 (3602)	14.26 (18.35)	3602 (3604)
3	5—15	5.84 (7.25)	3600 (3601)	14.74 (18.25)	3603 (3605)
4	10—5	1.57 (3.17)	3394 (3601)	8.89 (12.15)	3602 (3602)
5	10—10	1.16 (4.14)	2972 (3600)	23.28 (57.33)	3601 (3602)
6	10—15	3.58 (6.27)	3327 (3600)	18.33 (48.49)	3602 (3602)
7	15—5	1.04 (2.51)	2916 (3601)	8.82 (11.31)	3602 (3604)
8	15—10	1.23 (3.00)	3025 (3601)	10.59 (13.63)	3602 (3604)
9	15—15	4.73 (7.38)	3422 (3601)	10.28 (13.02)	3602 (3603)

durations. Finally, we compare the optimal solution of the proposed model with the solution implemented at our partner institution.

5.2.1 Sensitivity Analysis

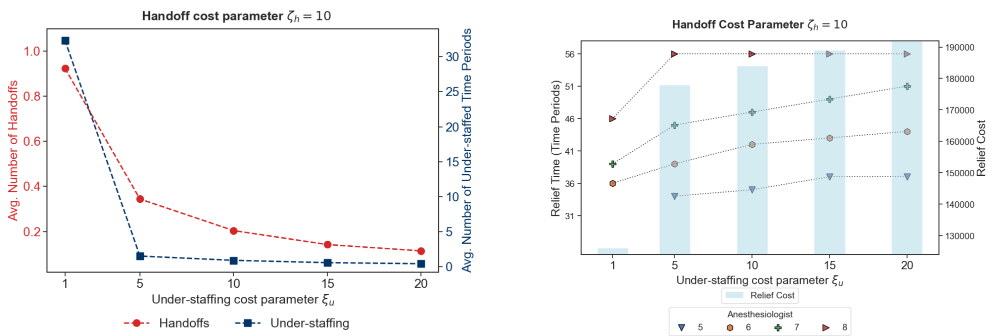
We analyze how the number of handoffs, the number of under-staffed time periods, and the relief times for anesthesiologists vary with respect to handoff and understaffing costs. For this subsection, we consider $\zeta_h = 1, 5, 10, 15, 20$ and $\xi_u = 1, 5, 10, 15, 20$. Figure 1a shows how increasing the handoff cost parameter ζ_h from 1 to 20, while keeping the under-staffing cost parameter ξ_u fixed at 10, affects the average number of handoffs and under-staffed time periods across all scenarios. Likewise, Figure 1b illustrates the corresponding changes in anesthesiologist relief times and total relief costs as ζ_h increases. Figures 2a and 2b present the same variations for a fixed handoff cost parameter $\zeta_h = 10$ and increasing under-staffing cost parameter ξ_u from 1 to 20.

In Figure 1a, both the average number of handoffs and the average number of under-staffed time periods decrease as the handoff cost increases. This occurs because anesthesiologists are scheduled for longer shifts and are relieved later in the day. Consequently, the anesthesiologist relief cost rises, as shown in Figure 1b. A similar trend is observed in Figures 2a and 2b, where increasing the under-staffing cost parameter ξ_u from 1 to 20 results in fewer handoffs and under-staffed periods, ultimately leading to higher relief costs. The key takeaway from these experiments is that decision makers can adjust the understaffing and handoff cost parameters to modify anesthesiologist relief times according to operational priorities. If decision makers aim to reduce the number of handoffs below a specified threshold, the resulting impact on anesthesiologist relief times—particularly their tendency to occur later in the day—can also be analyzed using the proposed model.



(a) (b)

Fig. 1: Trade-offs when increasing values of ζ_h (Remaining anesthesiologists were relieved at the end of the first time period)



(a) (b)

Fig. 2: Trade-offs when increasing values of ξ_u (Remaining anesthesiologists were relieved at the end of the first time period)

5.2.2 Value of the Stochastic Solution

We evaluate the impact of capturing uncertainty in surgery durations when scheduling anesthesiologists through Value of the Stochastic Solution (VSS). Specifically, we calculate the VSS $= \frac{MV - UB^{\texttt{SASH}}}{MV} \times 100$, where $UB^{\texttt{SASH}}$ is the best upper bound obtained from $\mathcal{F}_2$ and MV is the objective function value of $\mathcal{F}_2$ at the `Mean Value Solution` [42]. Table 8 presents the average (maximum) VSS across three instances for each combination of ζ_h and ξ_u, and $|\Omega| = 500, 750$. As shown in the table, accounting for uncertainty in surgery durations yields substantial improvements, with VSS values ranging from 35% to 67% across all cases. These findings underscore the value of adopting stochastic optimization approaches in operational settings where variability in task durations is significant. Moreover, the consistent magnitude of VSS across different combinations of handoff and understaffing costs suggests that the benefits of modeling uncertainty are robust to changes in cost structure.

Table 8: Average (max) %-VSS

Case#	Case ζ_h — ξ_u	$\lvert\Omega\rvert = 500$	$\lvert\Omega\rvert = 750$
1	5—5	35.19 (35.30)	35.20 (35.46)
2	5—10	53.65 (53.88)	53.58 (53.93)
3	5—15	63.85 (64.07)	63.79 (64.12)
4	10—5	39.21 (39.42)	39.19 (39.47)
5	10—10	55.77 (55.99)	55.74 (56.07)
6	10—15	65.15 (65.35)	65.09 (65.38)
7	15—5	42.88 (43.08)	42.87 (43.13)
8	15—10	57.71 (57.92)	57.70 (57.99)
9	15—15	66.35 (66.53)	66.31 (66.56)

5.2.3 Comparison with Current Practice

In this section, we compare the optimal solution of our proposed model, referred to as the `Opt` solution, with the `OR` assignments and relief times of anesthesiologists observed in the dataset obtained from our partner institution, referred to as the `CP` solution. To conduct this analysis, we focus on the surgical schedule of a specific day from our dataset, which includes 50 surgeries across 10 open `OR`s, with 8 available anesthesiologists. Further details about this schedule, referred to as Schedule C—including the specialty, planned start time, and the assigned `OR` of each surgery—are provided in Table A4 of Appendix A.

We compare the anesthesiologist relief cost (`RF`), expected handoff cost (`HO`), expected under-staffing cost (`UC`), and overall objective function value (`Obj`) of the `Opt` and `CP` solutions. We report $\eta_l = \frac{\text{Cost}_l^{\texttt{CP}} - \text{Cost}_l^{\texttt{Opt}}}{\text{Cost}_l^{\texttt{CP}}} \times 100$ for $l = \texttt{RF}, \texttt{HO}, \texttt{UC}, \texttt{Obj}$, where the higher η_l value implies better performance of the `Opt` solution. Tables 9 and 10 present the average (maximum) η_l values across three instances for $|\Omega| = 500, 750$, respectively. The `Opt` solution substantially outperforms the `CP` for all cases. For example, in Case 5 in Table 9, the `Opt` solution reduces anesthesiologist relief costs by 9.12% and lowers the expected handoff and under-staffing costs by more than 98%, leading to an overall cost reduction of 86.21%.

These results demonstrate that the proposed model can lead to significant operational improvements in anesthesiologist scheduling. By reducing costly and disruptive

Table 9: Average (max) %-Improvement over `Current Practice` ($|\Omega| = 500$)

Case#	ζ_h — ξ_u	$\eta_{\texttt{RF}}$	$\eta_{\texttt{HO}}$	$\eta_{\texttt{UC}}$	$\eta_{\texttt{Obj}}$
1	5—5	13.60 (14.93)	98.63 (99.05)	97.65 (98.29)	76.83 (76.90)
2	5—10	9.45 (9.45)	99.37 (99.39)	98.87 (98.95)	84.24 (84.33)
3	5—15	7.46 (7.96)	99.53 (99.57)	99.21 (99.28)	88.02 (88.10)
4	10—5	11.61 (11.94)	99.12 (99.16)	98.28 (98.44)	80.90 (80.97)
5	10—10	9.12 (9.45)	99.44 (99.46)	98.92 (98.95)	86.21 (86.28)
6	10—15	6.80 (7.96)	99.60 (99.61)	99.31 (99.37)	89.17 (89.24)
7	15—5	10.95 (11.44)	99.23 (99.25)	98.47 (98.60)	83.75 (83.81)
8	15—10	8.62 (8.96)	99.48 (99.52)	99.02 (99.13)	87.72 (87.79)
9	15—15	6.80 (7.96)	99.60 (99.61)	99.31 (99.37)	90.12 (90.18)

Table 10: Average (max) %-Improvement over `Current Practice` ($|\Omega| = 750$)

Case#	ζ_h — ξ_u	$\eta_{\texttt{RF}}$	$\eta_{\texttt{HO}}$	$\eta_{\texttt{UC}}$	$\eta_{\texttt{Obj}}$
1	5—5	14.59 (14.93)	98.43 (98.46)	97.40 (97.52)	76.88 (76.95)
2	5—10	9.45 (9.45)	99.41 (99.46)	98.93 (98.98)	84.27 (84.36)
3	5—15	8.13 (8.46)	99.50 (99.52)	99.17 (99.18)	88.04 (88.13)
4	10—5	12.44 (12.94)	98.91 (99.15)	98.14 (98.50)	80.92 (81.00)
5	10—10	9.12 (9.45)	99.45 (99.47)	98.99 (99.01)	86.23 (86.32)
6	10—15	7.46 (7.96)	99.56 (99.58)	99.27 (99.30)	89.19 (89.26)
7	15—5	10.95 (10.95)	99.21 (99.24)	98.58 (98.65)	83.77 (83.84)
8	15—10	9.12 (9.45)	99.45 (99.47)	98.99 (99.01)	87.75 (87.82)
9	15—15	6.30 (6.97)	99.65 (99.68)	99.42 (99.45)	90.14 (90.20)

events such as handoffs and under-staffing, the `Opt` solution offers a data-driven framework for enhancing workforce efficiency and patient safety in intraoperative settings. The reported improvements are based on scenarios generated using specialty-specific log-normal distributions of surgery durations fitted to observed data from our partner institution. Although the exact magnitude of reductions in the number of handoffs and understaffed periods depend on the variability and realization of surgery durations in different settings, the underlying modeling framework is broadly generalizable. It can be readily adapted to reflect surgery duration distributions, staffing policies, and constraints at other institutions.

6 Conclusion and Discussion

We have investigated key factors affecting the quality of intraoperative anesthesia handoffs through an online survey administered at our partner institution. The survey results revealed opportunities to improve the quality of information exchange during handoffs. As clinicians reported positive experience with teamwork, including communication, and were negative regarding staffing and work pace, we believe that improving staffing practices is an important approach to ensure safe, high quality handoffs. Guided by these insights, we formulate a two-stage stochastic programming model to determine optimal schedules for anesthesiologists that balance staffing costs with the number of handoffs and under-staffed periods under uncertainty in surgery durations. Given the daily surgery schedules in ORs, the proposed model determines the anesthesiologists' relief times and assignments to ORs.

We derive a monolithic reformulation of the proposed stochastic program, which outperforms the extensive form by achieving smaller optimality gaps and faster solution times. Our computational experiments are based on data from an academic medical center located in the Eastern United States. By comparing the outcomes of our model with the institution's current anesthesiologist scheduling practices, we find that the proposed framework can lead to substantial reductions in the number of handoffs and under-staffed periods. To assess the impact of uncertainty in surgery durations, we compute the Value of the Stochastic Solution, which shows that incorporating uncertainty in surgery duration results in more cost-efficient and reliable anesthesiologist scheduling decisions than those based on deterministic models. Moreover, we conduct sensitivity analyses to explore the tradeoffs between anesthesiologist staffing levels, the number of handoffs, and under-staffed periods.

The proposed scheduling model offers valuable insights for anesthesiology departments across multiple levels of decision-making. At the operational level, it can assist in day-to-day scheduling decisions, such as assigning anesthesiologists to ORs and determining relief times. At the strategic level, the model can be applied to historical or projected surgery volumes [43] to inform long-term planning. This includes assessing future staffing requirements, analyzing trends in anesthesiologist workload, and establishing baseline staffing benchmarks. For instance, using the model with projected surgery volumes for the upcoming year can help estimate the number of anesthesiologists needed to meet expected demand, identify ways to increase surgical capacity without expanding staff, and reduce instances of handoffs by ensuring adequate coverage. Ultimately, the model supports data-driven workforce planning and policy design, aiding in aligning anesthesiology staffing with institutional priorities over time.

In our computational experiments, we implement the proposed framework using specialty-specific log-normal distributions for surgery durations. However, additional features such as surgeon experience, case complexity, procedure type, and time of the day can be incorporated to improve surgery duration estimation [44]. Likewise, parameters related to handoff and under-staffing costs can be refined through empirical analysis of historical data. This enables the model to be tailored using institution-specific financial and operational inputs, enhancing both its precision and adaptability across diverse healthcare environments. For instance, handoff costs can be estimated by considering the expenses associated with systems implemented to maintain high-quality handoffs and the hospital's costs related to any adverse patient outcomes resulting from improper handoffs. Similarly, the cost of under-staffed time periods can be approximated by factoring in the cost of calling in on-call anesthesiologists and the additional expense of extending the relief times for on-duty anesthesiologists.

Future research will focus on tackling the integration of add-on surgeries into anesthesiologist scheduling. These surgeries, which are urgent and unplanned, are often added with little notice and can lead to significant delays in anesthesiologist relief times, increased handoffs, and more frequent periods of understaffing. Another promising extension of the proposed model involves integrating the scheduling of anesthesiologists and nurse anesthetists. Given their interdependence through the surgical schedule, a more advanced model could explicitly account for the coordination and synchronization needed between their schedules and `OR` assignments.

Appendix A Surgery Data

Table A1: Size of Schedules A and B

	Schedule A	Schedule B
Number of surgeries	80	70
Number of ORs	18	18
Number of anesthesiologists	14	14

Table A2: Surgery Schedule - Schedule A

Specialty		(OR, starting time period)
Type	Number of Surgeries	
Dentistry	5	(8, 1), (8, 14), (17, 1), (17, 10), (17, 20)
Gynecology	7	(2, 1), (2, 12), (2, 17), (6, 1), (6, 17), (6, 24), (6, 31)
Ophthalmology	18	(7, 10), (7, 17), (13, 1), (13, 5), (13, 11), (13, 17), (13, 22), (13, 27), (13, 31), (16, 1), (16, 3), (16, 6), (16, 8), (16, 11), (16, 13), (16, 19), (16, 26), (16, 30)
Orthopedics	11	(5, 1), (5, 8), (5, 14), (5, 21), (11, 21), (14, 1), (14, 8), (14, 19), (14, 27), (15, 1), (15, 12)
Otolaryngology	8	(1, 1), (1, 9), (1, 16), (3, 16), (3, 21), (12, 1), (12, 9), (12, 23)
Pediatric Ophthalmology	2	(7, 1), (7, 4)
Plastics	7	(4, 1), (4, 5), (4, 12), (4, 17), (4, 21), (4, 25), (4, 38)
Pediatric ENT	9	(3, 1), (3, 4), (3, 7), (3, 12), (10, 1), (10, 5), (10, 13), (10, 22), (10, 29)
Surgical Oncology	3	(11, 5), (11, 9), (11, 15)
Urology	10	(7, 26), (9, 1), (9, 8), (9, 15), (9, 19), (9, 23), (9, 33), (18, 1), (18, 5), (18, 9)

Table A3: Surgery Schedule - Schedule B

Specialty		(OR, starting time period)
Type	Number of Surgeries	
Dentistry	4	(8, 1), (8, 10), (17, 1), (17, 20)
Gynecology	9	(6, 1), (6, 7), (14, 1), (14, 10), (14, 19), (14, 29), (15, 1), (15, 14), (15, 19)
Ophthalmology	6	(7, 1), (7, 8), (16, 1), (16, 10), (16, 17), (16, 22)
Orthopedics	9	(2, 1), (2, 4), (2, 12), (2, 17), (5, 1), (5, 8), (5, 16), (5, 22), (15, 29)
Otolaryngology	7	(1, 1), (1, 5), (1, 11), (1, 29), (10, 7), (10, 12), (12, 17)
Pediatric Ophthalmology	15	(4, 1), (4, 4), (4, 11), (4, 18), (4, 23), (4, 26), (4, 31), (4, 34), (13, 1), (13, 4), (13, 14), (13, 19), (13, 24), (13, 29), (13, 34)
Plastics	4	(11, 1), (11, 5), (11, 9), (11, 16)
Podiatry	1	(5, 28)
Pediatric ENT	6	(3, 1), (3, 6), (3, 9), (10, 1), (12, 1), (12, 6)
Urology	9	(9, 1), (9, 6), (9, 12), (9, 18), (9, 25), (18, 1), (18, 7), (18, 19), (18, 26)

Table A4: Surgery Schedule - Schedule C

Specialty		(OR, starting time period)
Type	Number of Surgeries	
Dentistry	3	(9,1), (9,10), (9,20)
Gynecology	9	(5,1), (6,1), (5,4), (6,7), (6,11), (5,18), (6,21), (5,22), (5,28)
Ophthalmology	5	(7,1), (7,12), (7,20), (7,25), (7,31)
Otolaryngology	5	(1,1), (1,6), (1,11), (3,16), (1,21)
Pediatric Ophthalmology	7	(8,1), (8,4), (8,7), (8,13), (8,16), (8,19), (8,24)
Plastics	6	(3,1), (4,1), (3,3), (4,5), (4,10), (4,18)
Pediatric ENT	3	(3,13), (3,21), (3,26)
Urology	12	(2,1), (2,6), (10,7), (2,11), (10,13), (10,19), (2,20), (10,25), (2,25), (2,30), (10,30), (10,38)

References

[1] Abraham, J., Kannampallil, T., Patel, V.L.: A systematic review of the literature on the evaluation of handoff tools: implications for research and practice. Journal of the American Medical Informatics Association **21**(1), 154–162 (2014)

[2] Arora, V., Johnson, J.: A model for building a standardized hand-off protocol. The Joint Commission Journal on Quality and Patient Safety **32**(11), 646–655 (2006)

[3] Arora, V.M., Manjarrez, E., Dressler, D.D., Basaviah, P., Halasyamani, L., Kripalani, S.: Hospitalist handoffs: a systematic review and task force recommendations. Journal of hospital medicine: an official publication of the Society of Hospital Medicine **4**(7), 433–440 (2009)

[4] Solet, D.J., Norvell, J.M., Rutan, G.H., Frankel, R.M.: Lost in translation: challenges and opportunities in physician-to-physician communication during patient handoffs. Academic Medicine **80**(12), 1094–1099 (2005)

[5] Cooper, J.B., Long, C.D., Newbower, R.S., Philip, J.H.: Critical incidents associated with intraoperative exchanges of anesthesia personnel. Obstetric Anesthesia Digest **2**(4), 114 (1982)

[6] Perry, S.: Transitions in care: studying safety in emergency department signovers. Focus on Patient Safety **7**(2), 1–3 (2004)

[7] Abraham, J., Meng, A., Tripathy, S., Avidan, M.S., Kannampallil, T.: Systematic review and meta-analysis of interventions for operating room to intensive care unit handoffs. BMJ Quality & Safety **30**(6), 513–524 (2021)

[8] Riesenberg, L.A., Leisch, J., Cunningham, J.M.: Nursing handoffs: a systematic review of the literature. AJN The American Journal of Nursing **110**(4), 24–34 (2010)

[9] Mardis, M., Davis, J., Benningfield, B., Elliott, C., Youngstrom, M., Nelson, B., Justice, E.M., Riesenberg, L.A.: Shift-to-shift handoff effects on patient safety and outcomes: A systematic review. American Journal of Medical Quality **32**(1), 34–42 (2017)

[10] Kaye, D.R., Luckenbaugh, A.N., Oerline, M., Hollenbeck, B.K., Herrel, L.A., Dimick, J.B., Hollingsworth, J.M.: Understanding the costs associated with surgical care delivery in the medicare population. Annals of surgery **271**(1), 23–28 (2020)

[11] Abraham, J., Meng, A., Sona, C., Wildes, T., Avidan, M., Kannampallil, T.: An observational study of postoperative handoff standardization failures. International Journal of Medical Informatics **151**, 104458 (2021)

[12] Kitch, B.T., Cooper, J.B., Zapol, W.M., Hutter, M.M., Marder, J., Karson, A., Campbell, E.G.: Handoffs causing patient harm: A survey of medical and surgical house staff. The Joint Commission Journal on Quality and Patient Safety **34**(10), 563–570 (2008)

[13] Abraham, J., Pfeifer, E., Doering, M., Avidan, M.S., Kannampallil, T.: Systematic review of intraoperative anesthesia handoffs and handoff tools. Anesthesia & Analgesia **132**(6), 1563–1575 (2021)

[14] Epstein, R.H., Dexter, F., Gratch, D.M., Lubarsky, D.A.: Intraoperative handoffs among anesthesia providers increase the incidence of documentation errors for controlled drugs. The Joint Commission Journal on Quality and Patient Safety **43**(8), 396–402 (2017)

[15] Hyder, J.A., Bohman, J.K., Kor, D.J., Subramanian, A., Bittner, E.A., Narr, B.J., Cima, R.R., Montori, V.M.: Anesthesia care transitions and risk of postoperative complications. Anesthesia & Analgesia **122**(1), 134–144 (2016)

[16] Saager, L., Hesler, B.D., You, J., Turan, A., Mascha, E.J., Sessler, D.I., Kurz, A.: Intraoperative transitions of anesthesia care and postoperative adverse outcomes. Anesthesiology **121**(4), 695–706 (2014)

[17] Jones, P.M., Cherry, R.A., Allen, B.N., Jenkyn, K.M.B., Shariff, S.Z., Flier, S., Vogt, K.N., Wijeysundera, D.N.: Association between handover of anesthesia care and adverse postoperative outcomes among patients undergoing major surgery. Jama **319**(2), 143–153 (2018)

[18] Hu, J., Yang, Y., Li, X., Yu, L., Zhou, Y., Fallacaro, M.D., Wright, S.: Adverse outcomes associated with intraoperative anesthesia handovers: A systematic review and meta-analysis. Journal of PeriAnesthesia Nursing **35**(5), 525–532 (2020)

[19] Lee, S.-H., Phan, P.H., Dorman, T., Weaver, S.J., Pronovost, P.J.: Handoffs, safety culture, and practices: evidence from the hospital survey on patient safety culture. BMC Health Services Research **16**, 1–8 (2016)

[20] Sorra, J., Yount, N., Famolaro, T., Gray, L., et al.: AHRQ hospital survey on patient safety culture version 2.0: User's guide. Rockville: Agency for Healthcare Research and Quality (2021)

[21] Hose, B.-Z., Conn Busch, J., Lane-Fall, M., Bass, E.J.: Systematic approach for comparing team-based care processes. In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting, vol. 66, pp. 580–584 (2022). SAGE Publications Sage CA: Los Angeles, CA

[22] Greenberg, C.C., Regenbogen, S.E., Studdert, D.M., Lipsitz, S.R., Rogers, S.O., Zinner, M.J., Gawande, A.A.: Patterns of communication breakdowns resulting in

injury to surgical patients. Journal of the American College of Surgeons **204**(4), 533–540 (2007)

[23] Nagpal, K., Arora, S., Abboudi, M., Vats, A., Wong, H.W., Manchanda, C., Vincent, C., Moorthy, K.: Postoperative handover: problems, pitfalls, and prevention of error. Annals of surgery **252**(1), 171–176 (2010)

[24] Nagpal, K., Vats, A., Ahmed, K., Smith, A.B., Sevdalis, N., Jonannsson, H., Vincent, C., Moorthy, K.: A systematic quantitative assessment of risks associated with poor communication in surgical care. Archives of surgery **145**(6), 582–588 (2010)

[25] Horwitz, L.I., Parwani, V., Shah, N.R., Schuur, J.D., Meredith, T., Jenq, G.Y., Kulkarni, R.G.: Evaluation of an asynchronous physician voicemail sign-out for emergency department admissions. Annals of emergency medicine **54**(3), 368–378 (2009)

[26] Apker, J., Mallak, L.A., Gibson, S.C.: Communicating in the "gray zone": perceptions about emergency physician–hospitalist handoffs and patient safety. Academic Emergency Medicine **14**(10), 884–894 (2007)

[27] Breuer, D.J., Lahrichi, N., Clark, D.E., Benneyan, J.C.: Robust combined operating room planning and personnel scheduling under uncertainty. Operations Research for Health Care **27**, 100276 (2020)

[28] Guo, M., Wu, S., Li, B., Song, J., Rong, Y.: Integrated scheduling of elective surgeries and surgical nurses for operating room suites. Flexible Services and Manufacturing Journal **28**, 166–181 (2016)

[29] Latorre-Núñez, G., Lüer-Villagra, A., Marianov, V., Obreque, C., Ramis, F., Neriz, L.: Scheduling operating rooms with consideration of all resources, post anesthesia beds and emergency surgeries. Computers & Industrial Engineering **97**, 248–257 (2016)

[30] Xiang, W., Yin, J., Lim, G.: A short-term operating room surgery scheduling problem integrating multiple nurses roster constraints. Artificial Intelligence in Medicine **63**(2), 91–106 (2015)

[31] Di Martinelly, C., Baptiste, P., Maknoon, M.: An assessment of the integration of nurse timetable changes with operating room planning and scheduling. International Journal of Production Research **52**(24), 7239–7250 (2014)

[32] Di Martinelly, C., Meskens, N.: A bi-objective integrated approach to building surgical teams and nurse schedule rosters to maximise surgical team affinities and minimise nurses' idle time. International Journal of Production Economics **191**, 323–334 (2017)

[33] Lim, G.J., Mobasher, A., Bard, J.F., Najjarbashi, A.: Nurse scheduling with lunch break assignments in operating suites. Operations Research for Health Care **10**, 35–48 (2016)

[34] Guo, M., Wu, S., Li, B., Rong, Y.: Maximizing the efficiency of use of nurses under uncertain surgery durations: a case study. Computers & Industrial Engineering **78**, 313–319 (2014)

[35] Mobasher, A., Lim, G., Bard, J.F., Jordan, V.: Daily scheduling of nurses in operating suites. IIE Transactions on Healthcare Systems Engineering **1**(4), 232–246 (2011)

[36] Rath, S., Rajaram, K., Mahajan, A.: Integrated anesthesiologist and room scheduling for surgeries: Methodology and application. Operations Research **65**(6), 1460–1478 (2017)

[37] Tsang, M.Y., Shehadeh, K.S., Curtis, F.E., Hochman, B.R., Brentjens, T.E.: Stochastic optimization approaches for an operating room and anesthesiologist scheduling problem. Operations Research (2024)

[38] Kazemian, P., Dong, Y., Rohleder, T.R., Helm, J.E., Van Oyen, M.P.: An IP-based healthcare provider shift design approach to minimize patient handoffs. Health Care Management Science **17**, 1–14 (2014)

[39] Smalley, H.K., Keskinocak, P., Vats, A.: Physician scheduling for continuity: An application in pediatric intensive care. Interfaces **45**(2), 133–148 (2015)

[40] Sun, K., Sun, M., Agrawal, D., Dravenstott, R., Rosinia, F., Roy, A.: Equitable anesthesiologist scheduling under demand uncertainty using multiobjective programming. Production and Operations Management **32**(11), 3699–3716 (2023)

[41] Sinha, A., Bansal, A., Ozaltin, O., Russell, M.: A two-stage stochastic programming approach for CRNA scheduling with handovers

[42] Birge, J.R., Louveaux, F.: Introduction to Stochastic Programming. Springer, New York, NY (2011)

[43] Hassanzadeh, H., Boyle, J., Khanna, S., Biki, B., Syed, F.: Daily surgery caseload prediction: towards improving operating theatre efficiency. BMC Medical Informatics and Decision Making **22**(1), 151 (2022)

[44] Kayis, E., Wang, H., Patel, M., Gonzalez, T., Jain, S., Ramamurthi, R., Santos, C., Singhal, S., Suermondt, J., Sylvester, K.: Improving prediction of surgery duration using operational and temporal factors. In: AMIA Annual Symposium Proceedings, vol. 2012, p. 456 (2012)

Ethics Statement

All data used in this study were either de-identified prior to use or collected in compliance with institutional and national ethical standards.

Human Subjects

Institutional Review Board (IRB) approval for the survey study was obtained from the IRB at University of Illinois Urbana-Champaign, while the IRBs at Binghamton University and West Virginia University reviewed the work conducted at those sites and determined it did not meet the definition of human subjects' research. Informed consent for participation was obtained from all subjects involved in the survey study.

Data Privacy and Confidentiality

All data were handled with strict attention to confidentiality and privacy.

Conflict of Interest

The authors declare that they have no conflicts of interest related to this research.