



# Improving Clinic Operational Efficiency and Utilization with RTLS

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## Abstract

New sources of operational data are leading to novel healthcare delivery system design and opportunities to support operational planning and decision-making. Technologies such as real time locating systems (RTLS) provide a unique view and understanding of how healthcare delivery settings behave and respond to operational design changes. In this paper RTLS data from an outpatient clinical setting is leveraged to identify the appropriate number of scheduled providers in order to improve the utilization of the clinical space while balancing the negative effects of clinic congestion. The approaches presented pair historical utilization rates for the clinical space with scheduled provider and patient volumes to support scheduling decisions in an operationally flexible clinic design. These historical data are augmented with clinic staff observation logs to identify target utilization rates as well as high congestion levels. Results are presented for two approaches: one where utilization of clinical space is a key performance metric and another where the decision-maker may be risk averse toward the use of provider time and use a probabilistic approach to determine provider staffing levels.

**Keywords** RTLS · Outpatient clinic · Provider scheduling · Operations research

## Introduction

While substantial advances have been made since the Institute of Medicine and National Academy of Engineering have called for system-based improvements to healthcare delivery through information technology and systems engineering tools [1], the cost of medical care continues to rise [2]. Increasing efficiency in delivery systems is an imperative in improving operational performance, lowering costs, and creating systems responsive to patients' needs. As healthcare delivery systems continue to innovate to meet growing demand, new technologies and re-engineered flow processes are being embedded within care delivery settings. In order to maintain care quality and contain expenses, healthcare delivery systems must ensure high efficiency through judicious allocation and use of their available resources, both physical and human. However, traditional operational designs often assign specific resources, such as

exam rooms, to individual providers or staff. These traditional operational designs and resource allocation policies lack the flexibility which is afforded by new technology. As a result, multidisciplinary approaches to delivering care, which often require shared and flexible use of resources, are challenging to implement.

In balancing resource utilization with other performance and quality metrics, identifying appropriate ratios (e.g., rooms to staff) has been examined in a number of outpatient contexts. This question is commonly framed within two different operational plans. The most common approach is assigning specific exam rooms to providers [3] or outpatient procedure rooms to surgeons [4]. While higher ratios of rooms to providers improves performance and quality measures such as patients' waiting time and reduces provider idleness, it also comes at a significant cost of lower room utilization rates and perhaps lower patient volumes, depending on the number of providers and allocated exam rooms. As a result, this allocation often adversely affects the cost and efficiency of care delivered. Alternatively, the use of shared exam rooms has also been evaluated where multiple providers see patients in the exam rooms within the outpatient facility [5–7]. The aim of many of these studies is often focused on reducing waiting and length of stay (LOS) times while simultaneously improving exam room utilization.

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However, as described by Norouzzadeh et al. [6], implementing such shared exam room schemes is challenging in larger outpatient settings as inefficiencies resulting from providers finding and traveling to their patients reduce the intended benefits. To this end, Vahdat et al. [8] focus on the benefits of a hybrid allocation scheme where exam rooms are assigned to a subset of providers. This frame work is also extended to the allocation policies of medical assistants to exam rooms in the cardiovascular clinic setting studied. A novel operational recommendation is made in the exam room allocation scheme being dynamic and becoming more flexible, depending on the state of the clinic. The authors report that a majority of the operational benefits can be realized by implementing a hybrid approach, which is particularly important for clinic settings where it is operationally difficult to implement full flexibility of exam rooms, or a pooled allocation scheme. While implementing shared or flexible exam room policies is often logistically challenging, the advent of technologies such as real time locating systems (RTLS) has enabled operational staffing plans for larger flexible clinic spaces resulting in more providers being able to see patients with fewer rooms without foregoing efficient room utilization and maintaining low provider idle time [9].

Real time locating systems (RTLS) are a growing source for operational informatics in healthcare delivery settings as their adoption continues to increase in the healthcare industry [10]. Capable of tracking equipment and medical devices, RTLS technology is increasingly being used in patient flow related contexts by tracking the location of patients, providers, and staff. This equips healthcare delivery systems to incorporate RTLS-based information in real time decision making, such as where to allocate flexible staff to shore up long queues, as well as using the large amount of resulting data for analysis and modeling of tactical-level planning, such as exam room allocation and daily staffing decisions. Thus, RTLS technology has the potential to enable improvements in the efficiency and quality of care delivered in two ways. First, it affords the implementation of new operational models which require the use of real time location information. Second, RTLS data provides an understanding of a healthcare delivery setting's operational performance measures at a granular level previously unavailable.

In this paper we study the use of RTLS and the resulting informatics to support operational decision making. In contrast to traditional uses of RTLS where users are primarily interested in tracking equipment, people, and other resources in urgent situations or to maintain security, we focus on the use of operational data which can be abstracted from the RTLS across time. As a new source of operational informatics, RTLS data allows for the direct

and accurate evaluation of many important performance measures such as resource utilization, patient wait times, and provider idle times as opposed to traditional methods of evaluating such systems based on strong distributional assumptions or potentially biased estimates of the underlying processes.

### Clinic operational efficiency

Operational efficiency is used to describe the comparison between measurable inputs and outputs in a system. Within a clinic setting inputs may include available resources, staff, providers, or clinic space such as exam rooms. Measurable outputs may include the quality of care, patient throughput volumes, or revenue. Improving operational efficiency, therefore, involves improving the ratio of output to input, whether that be through decreasing necessary inputs or increasing the resulting output. Specific to an outpatient clinic where space and the number of exam rooms is fixed, an important component to improving operational efficiency requires better use of the available space.

Designing operationally efficient clinics is challenging in facilities where clinic space is shared and flexible. When resources such as exam rooms are pooled and not assigned to specific providers or staff, determining the right number of providers can be challenging as using the traditional exam room to provider ratios (e.g., 3:1 or 2:1) from assigned configurations result in an underutilization of space due to the economies of scale associated with larger pooled clinic designs.

RTLS offers a new solution to support operational decision making in determining the right number of providers to schedule within a flexible clinic space. RTLS provides an automated means of collecting operational data on clinic activity such as room utilization rates, provider idle time due to blocking, or patient wait times. Historically, such data has been challenging to collect due to inaccurate or biased estimates from stakeholders or time-consuming observational time studies which often result in small sample sizes. As a result, the new types of data available from RTLS position it as an appropriate data collection solution to support operational decision making to improve clinic operational efficiency.

While the design and use of new operational care models provide opportunities for increased efficiency and care delivery quality, capitalizing on such opportunities requires new staffing and resources allocation models in order to ensure best use of clinical space is realized. Traditional outpatient care design assigns specific resources and exam rooms to individual providers, the ratios of which have been previously examined [3, 4]. However, in newer clinical facilities with more flexible and shared capabilities, such

staffing levels and resource allocation policies need to be reexamined. The research in this paper is aimed to answer the operational question of how many providers should be scheduled in a clinic where exam rooms are flexible and shared in order to maximize exam room utilization while also ensuring that providers experience as little idle time due to fully utilized exam rooms as possible. To answer this question we use historical RTLS data along with staff observations of perceived congestion in the clinic. As a result, this provides a framework within which a novel source of operational informatics is leveraged to improve outpatient care delivery quality and efficiency.

## Literature review

In this section, an overview of related research is reviewed including the use of real time locating systems in healthcare settings and the discussion of staffing and resource allocation models for outpatient settings in the previous section is further detailed.

### RTLS in healthcare

While locating system technology has been slower to become adopted in healthcare as in other industries, common applications include tracking, identification, sensing, aiding interventions, and alert systems [11]. Real time locating systems (RTLS) have been traditionally deployed in healthcare settings to physically locate people or equipment [12, 13]. For example, RTLS has been used to find staff in large facilities during emergencies or track the location of patients to ensure safety.

An important application of RTLS technology which undergirds its use in operational decision making is its ability to automate many data collection processes. Cited as requiring significant time and conducive to measurement error [11], manual data collection efforts have been dispensed with in various settings in part due to the availability of RTLS technology. Examples include measuring hospital patient load in real time [14], supporting equipment auditing procedures [15], and improving input data collection for a simulation model [16].

While little has been reported with respect to clinic staffing decisions supported by RTLS technology, its use and resulting benefits have been demonstrated in improving operational processes within healthcare settings. Primarily, automated data collection from RTLS has provided process improvements through process redesigns. Process improvements typically focus on reducing non-value-added activities such as patient waiting, thereby improving patient satisfaction [17]. Such improvements are

particularly important in more urgent or care-intensive settings where patient safety may be at risk with delays and provide further motivation for the use of monitoring patient activities with RTLS [18].

### Staffing outpatient clinics

As more healthcare services are being provided in outpatient settings, as opposed to being admitted to a hospital, increasing attention has been given to managing outpatient clinics in an efficient way. Significant effort has been made in analyzing and developing models to improve the planning process prior to the clinic session. Examples include setting appropriate capacity levels for both staff and resources, designing scheduling templates to balance demand segments, and determining appointment schedules to mitigate patient wait time and provider idle time [19]. Outpatient delivery systems, and in particular specialty clinics, have a multitude of operational goals and objectives which are often competing [20]. Common performance measures include patient waiting time (both direct and indirect), length of stay or flow time, patient volumes, usage of overtime, resource utilization, and provider utilization or idleness. In outpatient specialty settings, high resource utilization is often a priority as opposed to minimizing patient wait time in settings with higher volumes of patients with lower acuity [19].

## Methods

The central aim of the work presented in this paper is to answer the question of how many providers should be staffed in a clinical environment with flexible exam rooms wherein exam room utilization is maximized and providers experience no, or minimal, idle time (blocked) due to their patients waiting to be roomed. To this end, an observational study design was pursued in order to evaluate the variability in patient volumes and clinic activity associated with varying levels of provider staffing. The data collected were from clinic days where staffing levels were observed naturally and were not manipulated. The study environment included a single site clinic setting with 21 exam rooms. Data were collected between November, 2017 and April, 2018.

Staff were asked to maintain observational logs of clinic congestion. The periods of collecting the observation logs were managed in a prospective fashion in order to coordinate avoiding clinic weeks with holidays, conferences, or other operational anomalies. Historical exam room utilization data was automatically collected from the RTLS and retrieved retrospectively. These two data sources were then

combined to identify a level of high utilization based on when staff observed that the clinic setting became congested and the system was stressed. Historical provider schedules were then paired with the utilization data from the RTLS to identify the provider staffing levels which resulted in exam room utilization rates which were high, but did not exceed the maximum based on staff observations.

### Study setting

The study in this paper is based on a clinic setting in the University of Minnesota's Clinic and Surgery Center (CSC). The specific clinic studied includes three primary specialties: cardiology, pulmonary, and multiple sclerosis. The three specialties share 21 exam rooms. During the check-in process, the patient receives an RTLS tracking device which will accompany the patient throughout their appointment. The RTLS tracking device accurately monitors the patient's location, space utilization, and time spent in various locations throughout the clinic space and building. Providers and staff have tracking devices while the physical spaces, such as exam rooms, have monitors to identify the location of the tracking devices.

The locating system also makes possible the implementation of the three specialties sharing a large set of exam rooms. The providers and staff make use of central office spaces between patient exams and are able to quickly identify their subsequent patient and exam room via a large monitor with RTLS information overlaid on a clinic map. This highlights an example of how RTLS not only facilitates the collection of new operational informatics, but also enables the implementation of new, more flexible, operational care models.

### Exam room utilization

Exam room utilization rates were automatically collected from the RTLS for each of the exam rooms in the clinic setting. Exam room utilization was defined as the portion of a room's available time during which the room was occupied by a patient. The implementation of RTLS used captures and calculates individual exam room utilization rates automatically. When the patient enters an exam room a sensor in the room detects a signal from the patient's RTLS tag. This enables the automated computation of exam room utilization rates. Utilization rates were retrieved for both the morning (AM) and afternoon (PM) portions of the clinic day as these segments align with how provider shift assignments are structured.

The average exam room utilization for each shift was then calculated manually by averaging shift utilization rates across all exam rooms. Exam room utilization data were

collected for a total of 62 days between November, 2017 and April, 2018 where 20 were in the fall, 22 in the winter, and 20 in the spring in order to capture seasonal variability in patient and provider volumes. During the spring data collection, it was discovered that the RTLS transceivers in three rooms were temporarily not working correctly and staff were asked not to use the three rooms for patient exams. As a result, 18 of the 21 rooms were used for the spring data collection whereas the fall and winter collections each contained data from all 21 rooms.

### Clinic congestion and provider blocking

In conjunction with measuring exam room utilization rates via RTLS, clinic congestion and the occurrence of provider blocking was measured using staff observation logs. Congestion and provider blocking are important operational measures which impact the providers' and the staff's ability to successfully manage the clinic, but are difficult to otherwise measure using RTLS. The clinic staff were asked to mark the perceived congestion in the clinic as Full, Partially Full, or Rarely Used for each of the three hallways where the 21 exam rooms are situated. Further, clinic staff were asked to mark when providers were blocked which resulted in being delayed or idle as patients not being able to be roomed due to no available exam room. This is considered an event which should rarely or never occur.

Staff observation logs were completed at the end of each shift (morning and afternoon). Each log comprised of two primary components. One was the perceived congestion level and the second was whether or not a provider was blocked during the shift. The three hallways were observed separately because the staff was instructed to make full use of the exam rooms in one hallway prior to using exam rooms in another. Collecting observed congestion for both shifts each day across multiple weeks allowed for the staff logs to include sufficient variability with respect to provider staffing levels and patient volumes.

### Analysis procedures

Descriptive statistics, linear regression, and a probabilistic analysis were used in making a range of operationally efficient provider staffing levels. Exam room utilization rates, perceived clinic congestion and provider blocking were analyzed using descriptive statistics and distributional visualizations including histograms and box plots. Linear regression was used to provide a predicted exam room utilization rates based on the number of providers scheduled in the clinic. The average exam room utilization from clinic days where the clinic congestion was marked as Full from the staff observation logs was calculated. Using the linear

regression model, the right number of providers to schedule is then determined based on achieving a predicted exam room utilization rate close to the calculated Full average.

A probabilistic analysis was used to determine the right number of providers to schedule for a risk-averse decision maker who may seek to avoid the occurrence of provider blocking based on a tolerable likelihood. A distribution of exam room utilization rate is assumed based on the number of providers scheduled. The probability of provider blocking is calculated probabilistically based on the exam room utilization rates which occurred when provider blocking was observed in the staff observation logs.

While maintaining high utilization of available exam rooms is desirable and the staff observation logs' characterization of Full helps identify desirable utilization rates in this regard, high occupancy also increases the risk of provider blocking. This is a particular risk on days where patient volumes are high for the number of providers scheduled or when no-show rates are especially low. To incorporate the risk of overstaffing providers in the clinic, a probabilistic analysis was included which aims to mitigate the likelihood of provider blocking in the decision-making process.

## Results

In this section we present the results of the analysis. First, we provide an overview of the RTLS and clinic descriptive data. Next, the results of the clinic staff observation logs are reported. These data are then combined to develop provider staffing level trends based on achieving high utilization of the exam rooms in the clinic. Finally, the results of a probabilistic analysis are presented in order to provide decision-makers the risk of a provider staffing level resulting in provider blocking or idleness.

### Patterns of room and provider utilization

Table 1 includes summary statistics for room utilization rates, provider staffing levels, and patient volumes. Descriptive statistics include mean, median, standard deviation,

minimum, and maximum values. Histograms for each measure are included in Fig. 1 and illustrate the variability of clinic activity captured in the data collected.

### Analysis of staff observations

The RTLS exam room utilization rates were used in conjunction with the clinic congestion measures from the staff observation logs to attribute specific exam room utilization rates to perceived clinic congestion levels. Staff observation logs included an entry for each shift and each clinic hallway. RTLS exam room utilization rates were averaged for each shift and hallway for which staff observations were made. The frequency of each of the three observation categories are displayed in Fig. 2. The average hallway RTLS exam room utilization was then merged with the staff observation for each shift and hallway. Each observation category's utilization distribution is displayed in the box plots in Fig. 3. While one can observe in Fig. 3 that the clinic staff observation categories generally trend with the RTLS utilization data, there is variability in the RTLS utilization rates which corresponded to each of the three clinic staff observation categories. Average utilization rates for Full, Partially Full, and Rarely Used observation categories were 0.55, 0.42, and 0.21, respectively.

### Achieving high exam room utilization

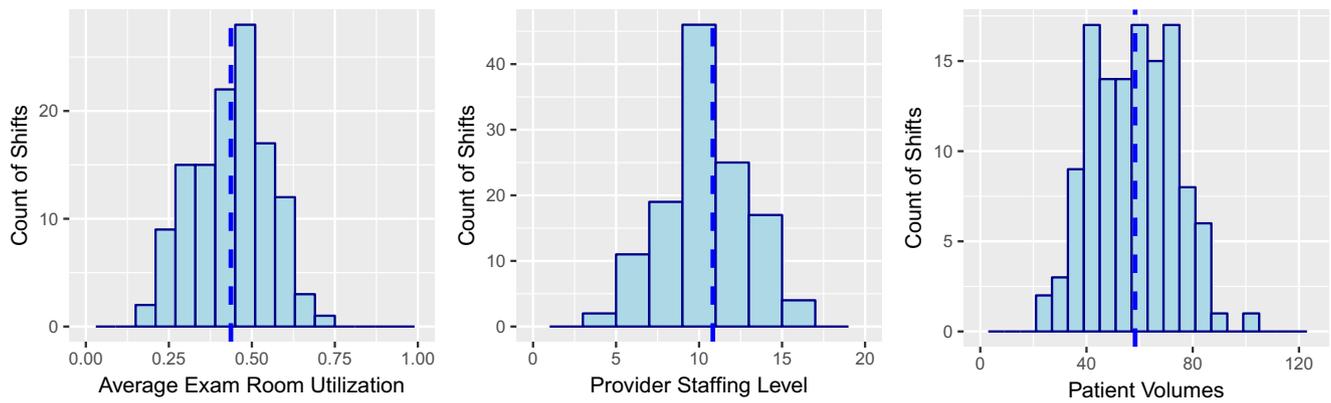
The average exam room utilization for clinic shifts where clinic staff observations of exam room usage were reported as Full provides a target average utilization rate based on the RTLS data. In order to identify the provider staffing level which achieves the target average, a linear regression model was fit using the RTLS average utilization rates and provider staffing levels. Figure 4 presents a scatter plot of these variables along with the resulting linear trend line.

The resulting linear model is defined in Eq. 1 where  $y$  represents the vector of average exam room utilization rates,  $x$  represents the vector of provider staffing volumes, and  $\epsilon$  is the vector of random errors. For example, using the parameters in Eq. 1 and the average exam room utilization of clinic shifts where staff reported the usage as Full (0.55),

**Table 1** Descriptive statistics are presented for average room utilization, and provider staffing levels

Measure	Mean	Median	StDev	Min	Max
Average room utilization	0.44	0.45	0.12	0.18	0.74
Provider staffing levels	10.83	11.00	2.53	5.00	17.00
Patient volumes	58.30	59.00	15.56	25.00	103.00

The summary statistics are based on 124 clinic shifts



**Fig. 1** Histograms are presented for Average Rooms Utilization, Provider Staffing Levels, and Patient Volumes. The dashed blue lines represent the distribution means

scheduling 14 providers during clinic shifts would result in high exam room utilization, on average.

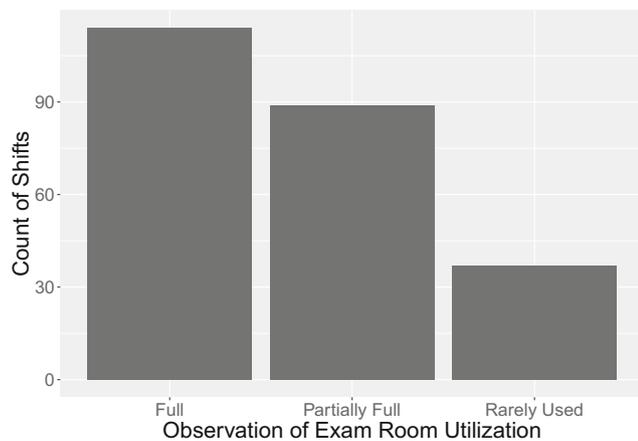
$$y = 0.066631 + 0.034178x + \epsilon \tag{1}$$

**Risk-averse approach**

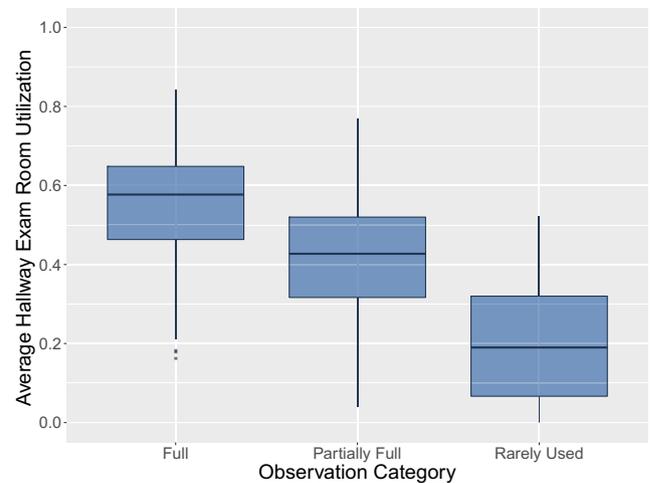
While the previous analysis and linear model provide a method to identify the provider staffing level which will result in a certain exam room utilization, on average, the variability depicted in the scatter plot in Fig. 4 illustrates the possibility for a specific provider staffing level to result in a range of exam room utilization rates during a given shift. This motivates an alternative approach to determining provider staffing levels based on the decision-makers risk tolerance for a clinic shift having either very high or very low exam room utilization rates. For example, when exam room utilization is very high and the clinic becomes

congested, this may often result in wasted provider idle time as they become blocked from seeing their patients. Here, we present a risk-based approach which incorporates the decision-maker’s tolerance for such events (e.g., provider blocking may be tolerable 5% of the time as a trade off to maintaining high exam room utilization, on average).

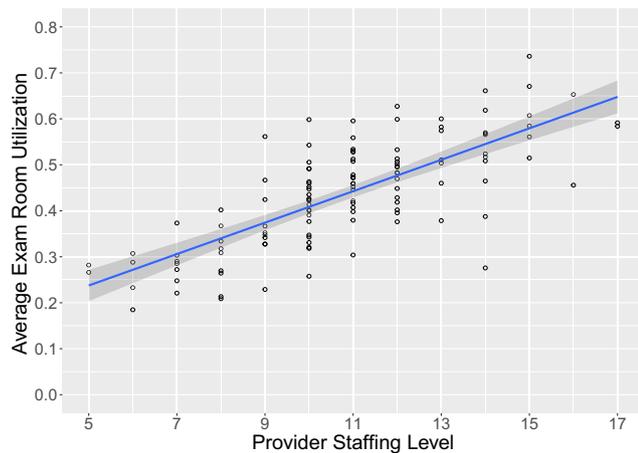
We assume, for demonstration, that clinic shift exam room utilization rates for a given provider staffing level,  $n$ , are normally distributed with a mean of  $\mu_n$  and is calculated from Eq. 1. The standard deviation,  $\sigma_n$ , is set to be proportional with respect to the coefficient of variation ( $CV_{All}$ ) of the entire exam room utilization rate sample across all provider staffing levels. I.e.,  $CV_n = \frac{\sigma_n}{\mu_n} = CV_{All} = \frac{\sigma_{All}}{\mu_{All}}$ . This is due to having smaller and variable sample sizes for specific provider staffing levels. The likelihood of a clinic shift’s average exam room



**Fig. 2** The frequency of each classification of exam room utilization as observed by the clinic staff is presented where observations were based on the utilization and congestion of one of three hallways in the clinic



**Fig. 3** The distributions of the average hallway exam room utilization for each observation category are displayed in the box plots where the upper and lower ends of the boxes represent the 75th and 25th quartiles, respectively, and the line in the box is the median value



**Fig. 4** Average exam room utilization rates are plotted with the number of providers seeing patients in the clinic during the shift. A linear trend line along with a 95% confidence interval is included

utilization being greater than or equal to a predetermined threshold,  $\hat{y}$ , can be calculated with the complementary cumulative distribution function. Suppose  $\hat{y} = 0.74$ , which was the maximum observed average exam room utilization, then the aim is to identify a provider staffing level which results in a tolerable probability of the average exam room utilization exceeding 0.74,  $P(y \geq \hat{y} = 0.74)$ . The resulting probabilities are presented in Table 2 for provider staffing levels ranging from 10 to 17.

In the previous section, scheduling 14 providers was determined as the right staffing decision as this was expected to result in an average exam room utilization rate of 55%, which was identified desirable based on the staff observation logs and RTLS exam room utilization rates. In Table 2, it is shown that staffing 14 providers results in 0.09 probability that the clinic will experience blocking. The clinic manager can then decide if this is an acceptable likelihood or change their staffing decision based on the probabilities included in Table 2 along with the expected utilization rates in Fig. 4.

### Discussion

Applications of RTLS technology in healthcare have largely focused on managing inventory, tracking people

and expensive assets, and identification of patients or care providers. However, as the technology continues to advance in accuracy and temporal capability, new opportunities are afforded in clinical operations management. The ability to better understand system behavior through RTLS data allows for the development of new operational interventions within the care delivery. Previous operational examples include time use studies of nurses [21, 22], the evaluation of provider face time with patients [23], and modifying provider behavior with RTLS-based data [24]. As adoption of the technology grows, it is reasonable to expect that new uses will have implications on the planning and design of clinic operations, particularly as it becomes more closely tied to health record data and outcomes.

In this paper, we presented a method for making provider staffing level decisions which balance exam room utilization and provider efficiency using operational RTLS data. The operational RTLS data was paired with clinic staff observation logs to identify the exam room utilization rates which resulted in high utilization of the clinic space. The RTLS data from the clinic shifts which were identified as having high utilization by the clinic staff were then matched with the corresponding provider staffing levels to determine the appropriate provider staffing levels which result in high utilization of the clinic exam rooms. Provider staffing levels were determined based on an expected exam room utilization rate based on a linear model as well as a probabilistic approach for cases where the decision maker may be risk-averse toward events which occur when the clinic is overly congested, such as provider blocking. Together, these provide administrators or managers the expected exam room utilization rate as well as the probability of provider blocking for a given provider staffing level. For example, if 14 providers were scheduled during a clinic shift, the average exam room utilization expected would be 0.55 while the probability of provider blocking occurring is 0.09, where provider blocking is assumed to occur if utilization rates are 0.74 or higher. That is, provider blocking may occur in approximately one of every ten half day clinic shifts.

Traditional outpatient resource allocation policies examined in the literature have focused on assigning discrete resources such as exam rooms to a specific provider or staff. Such policies have been evaluated by comparing different provider to exam room ratios. Simulation analyses have

**Table 2** The probability of provider idle time and blocking occurring as a result of average exam room utilization rates exceeding a threshold of 0.74 are presented for each provider staffing level

Provider staffing level	10	11	12	13	14	15	16	17
Blocking probability	≤ 0.01	0.01	0.02	0.04	0.09	0.15	0.22	0.29

studied the effects of dedicated, or assigned, exam room policies with 1:1, 1:2, and 1:3 ratios (provider: exam rooms) [3, 4]. More exam rooms per provider is generally desirable for the provider as this reduces their chances of being idle due to blocking. However, more exam rooms per provider also reduces the utilization of exam rooms resulting in lower efficiency of the fixed resources. In contrast to previously reported results based on dedicated exam room policies, the flexible design and operational decision analyzed here provides for improved efficiency through higher utilization of exam rooms without sacrificing the likelihood of provider blocking. The effective provider-to-exam room ratio is 2:3 based on the predicted exam room utilization results where 14 providers are scheduled within 21 exam rooms.

The series of analyses and approaches presented in this paper are accessible in their methods and flexible in their implementation for use in a broad range of clinical settings by managers and administrators. However, there are two requirements in order to make the recommendations possible. The first is having an RTLS system in place along with consistent use by its users. In this study, patients were the only users required, though other projects may make use of providers and staff using the technology. While it is unlikely that this specific operational analysis justifies an investment in the technology by itself, the value proposition for RTLS in clinical settings continues to grow with other uses. However, as previous research has commented, RTLS and related technology should be viewed as a cost-savings opportunity rather than one of increasing revenues [24]. Second, the presented method relies on the clinic's use of a *first room up* use of allocating exam rooms to providers. In this operational design, providers are not assigned specific exam rooms, but the next arriving patient is simply brought to the next available room and their provider is then notified where their next patient is based on the patient's RTLS beacon. This flexible exam room allocation policy increases exam room utilization, but also requires a method to identify the appropriate number of providers.

This study and approach have limitations that are important to point out. First, the accuracy of the RTLS data is subject to the extent to which it is consistently used by providers, staff, and patients as well as the technology's spatial and temporal abilities to measure clinic activity durations. As a result, it is possible that the utilization rates reported here are lower bounds on the true values. For example, if a provider's clinic shift or a patient's visit was not captured via the RTLS the rooms which they occupied may appear as being unused. Second, in determining what utilization rate was classified as high, the clinic staff's observation log may be a subjective or biased assessment of the clinic's congestion as they are asked to try to classify the entire clinic shift whereas in reality the clinic's congestion likely fluctuates during the shift.

## Conclusions

This paper makes contributions to the research literature related to RTLS, healthcare operations management, and operational informatics in the following ways. First, we present a novel use of RTLS technology and informatics to inform operational planning. As previously discussed, the use of RTLS in healthcare has been predominantly for the purpose of tracking people or important resources in real time. However, we demonstrate that the same technology and data has meaningful implications on improving the efficiency and quality of care delivered in outpatient settings. Second, the methods used in this work provide a framework for using operational informatics to make provider staffing decisions in flexible clinic settings. As new facilities become more prevalent and the use of technologies such as RTLS are widely used, the framework presented here provides administrators an adoptable method for operational decision support and planning. Finally, while many efficiency or quality improvement focused efforts use only operational data, we pair the operational informatics from RTLS with staff-based perceptions of the state of the clinic setting to identify the utilization levels at which the clinic as a system becomes stressed, which is otherwise difficult to directly measure. Together, these contributions represent a means of leveraging new operational informatics to improve the efficiency and quality of care delivered in outpatient settings.

## Compliance with Ethical Standards

**Conflict of interests** The authors declare that they have no conflict of interest.

**Ethical approval** This article does not contain any studies with human participants performed by any of the authors.

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