



A simulation study of touch-free automatic alcohol-based handrub dispensers on hand hygiene disruption in healthcare settings

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ABSTRACT

Automatic dispensers of alcohol-based handrub (ABHR) have been widely adopted in healthcare facilities to maintain hand hygiene (HH). A proper supply of energy and refill is crucial to ensure uninterrupted access to hand sanitizing and minimize workflow disruption and inefficiencies. Various energy design and refill replenishment technologies have emerged with promising potential to eliminate HH disruptions. However, there is a lack of quantitative studies assessing the design impact on hand hygiene performance in healthcare settings. In this paper, we employ data-driven discrete-event simulation (DES) to evaluate the long-term performance of various energy designs of automatic dispensers in healthcare facilities. We analyze 7 years of historical usage data from 4 US hospitals and identify the usage patterns, which serve as the input traffic for our simulation model. We then estimate the workflow disruption caused by different types of dispensers over a 6-year period, in terms of the number of missed HH opportunities, battery replacements, and duration of downtime. The simulation results suggest that the differences in performance are significant among dispenser types. In high usage, the number of missed HH opportunities caused by refill depletion ranges from 403.1 to 1232.4, and total downtime ranges from 0 to 96.3 h. Implementing proactive maintenance measures, such as service refill alerts, can greatly reduce the chances of ABHR depletion, resulting an 81.6 % decrease in HH disruptions for a single dispenser in high usage. Therefore, healthcare facilities should consider the variations in dispenser design, including the energy management system. They should also carefully study dispenser usage patterns to implement optimized policies and practices for ABHR refill maintenance to minimize overall missed HH opportunities.

1. Introduction

Automatic alcohol-based hand rub (ABHR) dispensers are widely adopted for hand hygiene (HH) in healthcare facilities due to their easy access, ability to eliminate direct contact, and their association with reduced transmission of pathogens and lower hospital-acquired infection rates (Jefferson et al., 2023). Maintaining the stable operation of ABHR dispensers is crucial to maximizing these benefits, but often faces challenges related to the energy and refill supply of the dispensing system. In a hospital with hundreds or thousands of dispensers exhibiting varying usage patterns, maintaining proper energy and refill levels for all of them can be challenging. Inoperable dispensers, resulting from dead batteries and depleted refills, create pain points that lead to

workflow disruption and inefficiencies in healthcare facilities. When healthcare workers cannot access ABHR at their first-choice dispenser, they may spend more time searching for another one or even skip sanitizing, increasing the risk of pathogen transmission. The unavailability of ABHR dispensers can also negatively impact visitors' experiences at a facility, fostering frustration and a perception that the hospital is not adequately prioritizing health and safety. Therefore, ensuring proper energy design and refill maintenance is crucial to guarantee uninterrupted access to hand sanitizing and sustain optimal hand hygiene performance in hospitals.

To this end, various energy and refill replenishment technologies have emerged, aiming to ensure reliable and consistent performance of automatic ABHR dispensers. Many design the supply power by using

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large batteries, intending to last for the expected dispenser lifespan (typically over 5 years). However, over a dispenser's lifetime, batteries may wear down faster than anticipated for various reasons. A newer power supply solution, Energy-On-the-Refill (EOR), involves attaching a relatively small battery to the refill bottle, ensuring the primary power supply of a dispenser is replenished when a refill is replaced. Regarding ABHR refill maintenance, many designs include a warning line or a warning indicator on the refill bottle to alert when the liquid is near depletion. However, due to inefficient and poor management of some facilities, it can take housekeeping personnel days or weeks to discover. To avoid service disruption due to a lack of maintenance, real-time service alerts have been proposed to notify housekeepers for replenishment when ABHR level is low. Although these technologies show a promising potential to eliminate hand hygiene disruptions, little quantitative evidence is available on the consequences of using these different designs.

The objective of this study is to assess the impact of dispenser designs on HH performance. We evaluate various designs by estimating the number of missed HH opportunities and downtime caused by dead batteries and empty refills. Observing dispensers' failures throughout their lifespan is impractical given the relatively long duration and extensive scope of the system. Therefore, we employ discrete-event simulation (Kelton et al., 2015) to compare dispensers of various designs. To the best of our knowledge, no simulation studies have been conducted to evaluate the performance of automated ABHR dispensers with real-world usage patterns in healthcare settings. The research aims are formalized into 1) building mathematical models to capture the daily operation of automated ABHR dispensers under uncertain demand, 2) identifying factors affecting dispenser reliability, and 3) studying and comparing the reliability of different dispenser designs in various healthcare facilities.

Our study contributes to the literature of hand hygiene research from multiple aspects. First, ABHR dispensers are recommended globally as the standard for hand hygiene practices in healthcare environments (Boyce & Pittet, 2002; Glowicz et al., 2023; World Health Organization, 2009; World Health Organization, 2022). They are also vital for public health in other settings. For instance, installing ABHR dispensers in schools can reduce absenteeism by up to 59 % (Bloomfield et al., 2007; Priest et al., 2014). Besides, the use of ABHR has been shown to lower the risk of germ transmission and infection rates in military (Mott et al., 2007), office buildings (Arbogast et al., 2016; Kurgat et al., 2019), and athletic training environments (Labelle et al., 2020).

Second, this study provides, for the first time, a holistic evaluation at the hospital scale, based on real-world traffic, of the HH performance of different dispenser designs with varying energy/refill configurations. We employ inventory models to keep track of the battery energy and the refill volume and capture the operation of different dispenser designs using discrete-event simulation. We analyze the usage patterns of the dispensers in four different types of hospitals from real-world data, which are then used as input traffic to drive our simulation. We evaluate the duration of downtime and the number of missed hand hygiene opportunities due to dead batteries, and that due to empty refills, and compare the performance of different designs. Our results suggest that healthcare facilities should carefully compare alternative dispenser designs and technologies to ensure uninterrupted hand hygiene service.

Third, we also study the effectiveness of the refill service alert, a new form of proactive maintenance for dispenser refills, and evaluate the trade-off between hand hygiene performance and refill waste. Our results indicate that implementing such maintenance alerts helps reduce missed hand hygiene opportunities due to empty refills, and the optimal trigger threshold for the alert depends on the usage pattern of the dispenser. Additionally, exogenous factors such as dispenser usage patterns should also be considered to develop optimal policies for battery placement and refill maintenance.

The remainder of this paper is organized as follows. In Section 2, we provide a brief review of previous research on ABHR dispensers, battery

models, and the application of discrete-event simulation in healthcare. Section 3 details our research methodology. First, we overview dispenser usage data from hospitals and technical specifications of various dispenser designs. Then, we introduce the mathematical models for dispenser daily operation and usage patterns, followed by our discrete-event simulation models. Verification and validation procedures are also discussed in this section. In Section 4, we present the simulation results, which include a comparison of dispenser designs in terms of HH misses, and an evaluation of the efficiencies and trade-offs associated with different refill maintenance policies. Section 5 discusses the importance and limitations of this work. Finally, concluding remarks are made in Section 6.

2. Literature review

Our research intersects with several streams of literature, encompassing ABHR dispenser and hand hygiene research, battery modeling, inventory models, and discrete-event simulation. Below, we offer a concise overview of each stream, drawing upon representative examples from existing literature and contextualize our research within the broader landscape of these streams.

2.1. ABHR dispenser and HH compliance

Studies on the performance of ABHR dispensers have predominantly been conducted in laboratory settings. One study has shown that touch-free dispensers significantly increase hand hygiene compliance compared to manual dispensers in two units of a large pediatric hospital (Larson et al., 2005). Other studies suggest that utilizing touch-free hand hygiene dispensers contributes to improved hand hygiene performance and facilitates compliance monitoring measurement (Boyce et al., 2019; Arbogast et al., 2023). In addition, research underscores the importance of ABHR dispenser design in ensuring reliable and consistent performance, delivering the right amount of ABHR when needed, which not only influences the effectiveness of ABHR (Macinga et al., 2013; Price et al., 2022) but also affects healthcare workers' hand hygiene compliance (Greenaway et al., 2018). A recent Cochrane Review highlights hand hygiene as one of the most important interventions for preventing pathogen transmission and reducing the risk of respiratory viruses (Jefferson et al., 2023).

2.2. Battery models

The state of charge (SOC) of a battery, representing the level of charge relative to its capacity, is highly nonlinear due to its complex internal electrochemical dynamics, and susceptibility to factors such as temperature, cycle times, aging, etc. Numerous battery models have been developed, see, e.g., (Zhou et al., 2021) and references therein. The survey categorizes the models into three main types: electrochemical mechanism models, equivalent circuit models, and data-driven models. Electrochemical mechanism models attempt to fully capture a battery's internal physical and chemical processes with electrochemical power and transmission equations, see, e.g., (Doyle et al., 1993; Zhang et al., 2000). Equivalent circuit models simulate the dynamic characteristics of a battery with circuit networks, see, e.g., (Johnson, 2002; Li et al., 2021). Data-driven models, including the machine learning approach, avoid directly modeling the actual battery system and utilize external characteristic parameters for SOC estimation, see, e.g., (Li, 2020). This approach can capture the non-linearity of battery SOC and can be generalized to different battery types, but it also requires a large amount of battery testing data. The most used data-driven method is the direct measurement method, where the goal is to estimate battery SOC using measured parameter variables correlated with the battery, such as voltage and current. Machine learning models, such as neural networks, support vector machines, and deep learning, are often employed for SOC estimation (Wei et al., 2018; Yang et al., 2018). In our research, we

adopt the data-driven approach to model dispenser battery consumption.

2.3. Discrete-event simulation and inventory models in healthcare

Discrete-event simulation has found widespread application in the study of healthcare systems, with various uses in emergency departments, inpatient facilities, outpatient clinics, and other hospital units, including intensive care units, pharmacies, operating rooms, and therapy. A comprehensive survey by Günel and Pidd (2010) provides insights into the diverse applications of discrete-event simulation in healthcare, with numerous references therein. Many studies in this domain aim to improve the operational performance of a system in healthcare facilities by facilitating better decision making and planning. Common applications include the scheduling of healthcare workers and the sizing and planning of resources such as beds, rooms, and staff. For example, discrete-event simulation has been employed to evaluate emergency medical location models (Ünlüyurt and Tunçer, 2016) and to model patient flows in an orthopedic clinic (Baril et al., 2014; Bean et al., 2019). To the best of our knowledge, this is the first study using discrete-event simulation to capture the design impact on hand hygiene performance in healthcare settings.

Our model is also related to inventory management research, as seen in works such as Zipkin (2000). We model the ABHR inventory of a dispenser as a nonperishable good that is only consumed by usage, while the battery energy of a dispenser is treated as a perishable good that decreases with both usage and deterioration (due to idling and self-discharging). A recent survey can be found in Karaesmen et al. (2011), which categorizes the literature into periodic and continuous review inventory control. The traditional manual check for battery functionality and ABHR refill emptiness can be viewed as a periodic review, whereas the real-time service alert represents a continuous review approach. In this work, since determining the optimal review and maintenance policy for each device is not our goal, we simply set the inspection interval based on what is used in practice and focus on comparing the design impact of different devices using discrete-event simulation.

3. Research methodology

We now describe our methodology for evaluating the HH performance of ABHR dispensers. Our approach is based on data-driven discrete-event simulation, which consists of the collection and analysis of dispenser usage data, the development and simulation of dispenser models, and the implementation of maintenance policies for batteries and refills. We perform input analysis with statistical software R (version 4.2.0) and build dispenser models within simulation software Arena (Rockwell Automation, version 16.2).

3.1. Data: Usage log history and dispenser parameters

Seven years of usage data (November 2014 – June 2021) is pulled from the AHHMS (Automated Hand Hygiene Monitoring System) installed in four US hospitals equipped with automatic sanitizer dispensers from GOJO¹ Industries. Table 1 summarizes information of the test facilities including hospital types, number of monitored dispensers and dispensing events, obtained from the AHHMS data. Note that the AHHMS data we use does not cover all the dispensers because only a subset is attached to the monitoring system. The AHHMS data also contains activities of soap dispensers, but in this study, we only use the

part of ABHR dispensers.

Seven automatic dispensers from different manufacturers are considered in this study. Technical specifications of these dispensers related to dispensing are measured using laboratory testing by experienced electrical engineers at GOJO, with calibrated equipment and validated test methods. The energy measurements are completed on three replicates and the average values are reported in Table 2.

3.2. Simulation models

There are three interdependent components in the modeling of a dispensing system: 1) the dispenser, 2) the usage pattern, and 3) the maintenance policies. The arrival of a usage request triggers the consumption of battery energy and ABHR, and the maintenance policies determine the timing of replenishment for the batteries and refills.

3.2.1. The dispenser: An inventory model

We model a dispenser's battery energy and ABHR volume as its inventories consumed by users over time. The status of a dispenser at time t is represented by a pair $(E(t), L(t))$, where $E(t)$ and $L(t)$ denote respectively the energy and sanitizer liquid inventory levels at time t . The dispenser stops working if either of the inventories goes empty (or below certain thresholds). A user arriving at a non-functioning dispenser has no access to hand sanitizing. Such a failed dispensing event will be recorded as a *hand hygiene miss*. Next, we describe the inventory dynamics using time-dependent differential equations.

Each time there is a successful dispense, the ABHR inventory $L(t)$ will decrease by an amount l_d , which is the dispenser's default *dispense volume per actuation*. We assume that the dispense volume is independent of time, the environment, and the user. A refill maintenance will replace the current bottle (possibly incurs wastage) with a new one of full volume L_0 . The refill volume L_0 and the dispense volume per actuation l_d for different dispenser types are provided in Table 2.

The evolution of the ABHR inventory $L(t)$ in one refill cycle, assuming a refill replacement just occurred at time t_0 , and the dispenser has sufficient power, can be described as follows:

$$\begin{cases} \frac{\partial L(t)}{\partial t} = -l_d a(t) \\ L(t_0) = L_0 \end{cases} \quad (1)$$

where $a(t)$ denotes the user arrival rate at time t . Based on our analysis of the usage data, the arrival process $\{a(t), t \geq 0\}$ of dispensing events is typically nonstationary. Note that we model ABHR as a nonperishable good, whose inventory is only reduced by usage.

The evolution of the energy inventory $E(t)$ is a more complex process. The total energy consumption of a dispenser is categorized into three components: *dispense energy*, *idle energy*, and *self-discharge energy*. The dispense energy represents the energy used during each dispensing operation. Idle energy is the energy consumed to maintain a dispenser in standby/idle mode when not in use. This is determined by multiplying the idle power by the duration the dispenser remains in idle mode. Self-discharging is a natural battery aging process that diminishes the stored battery charge through internal chemical reactions. To quantify the energy consumption of these activities, we utilize joule (J) as the unit of energy. It is important to note that 1 J of energy is consumed when 1 W of power is sustained for 1 s. In other words, power is the rate of consuming energy.

Let E_0 denote the initial battery capacity of a dispenser, e_d the energy consumed per dispense, e_i the idle power (idle energy consumed per second), and e_s the self-discharge energy per second. We can describe the evolution of the energy inventory $E(t)$ in a battery's lifetime as follows:

¹ GOJO Industries, Inc., is a privately held manufacturer of hand hygiene and skin care products based in Akron, Ohio, USA. One of its most well-known products is *Purell* hand sanitizer. It offers electronic hand hygiene dispensing and monitoring systems for medical institutions.

Table 1

Summary of facility information and dispense event details to inform modeling.

Facility code	Hospital type	Patient rooms	Total # of dispensers ¹	# of ABHR dispensers	Data time range	Total ABHR dispenses ²	Average daily ABHR dispenses ³
1	Adult, Academic medical center	536	2,456	685	11/11/2014—06/10/2021	31.6 million	13,141
2	Adult, Veterans	118	794	275	01/31/2017—06/10/2021	10.1 million	6,379
3	Pediatric, Academic medical center	106	943	273	01/12/2015—06/10/2021	9.2 million	3,947
4	Adult, Community	66	354	161	12/06/2016—06/10/2021	6.9 million	4,215

¹ This total includes soap dispensers used for hand washing and ABHR dispensers that are equipped with automated monitoring.² Total dispenses for all ABHR dispensers during the entire time range.³ This is the average number of ABHR dispenses daily for the facility for all dispensers.**Table 2**

Dispenser testing data related to dispensing.

Device Code	Manufacturer, Model	Refill Volume (mL)	Total Battery Joules (J)	Energy per Dispense (J)	Average Dispense (mL)	Idle Power (uW)
1	GP, EnMotion	1,000	267,370	1.44	1.08	358.4
2	Medline, Spectrum	1,000	120,800	2.02	0.78	1255.8
3	SCJ, Ultra	1,000	264,640	2.15	0.75	480.0
4	Scotts, Essential	1,200	101,630	1.11	0.67	699.2
5	Ecolab, NEXA	1,200	190,300	1.71	0.96	693.1
6	GOJO ES-10	1,200	38,210 (APS) + 11,841 (EOR) ¹	2.22	1.25	267.5
7	GOJO, LTX	1,200	231,900	2.50	1.24	885.3
8	Device 7 equipped with refill service alert technology					

¹ For GOJO ES-10, 38,210 J comes from the auxiliary power supply (APS) in the device and 11,841 J comes from the battery on the refill bottle (EOR, or Energy On the Refill).

$$\begin{cases} \frac{\partial E(t)}{\partial t} = -e_i - e_d a(t) - e_s E(t) \\ E(0) = E_0 \end{cases} \quad (2)$$

There are other factors that affect energy consumption, for instance, operating temperature, aging of batteries and wear of the dispensing system, etc. For simplicity, we focus on the major factors and believe that our energy model is sufficient as an initial attempt to this simulation study. From the perspectives of inventory modeling, equation (2) corresponds to the evolution of a perishable good since the battery energy incurs losses not only due to usage but also deterioration (idling and self-discharging), see, e.g., [Macías-López et al. \(2021\)](#).

It is worth mentioning that the battery capacity and the refill level affect the quality of a dispense *interdependently*. When the battery energy is plentiful but the refill level $L(t)$ is near depletion, the user will get an “empty” dispense – meaning a dispense without sanitizer. In this scenario, we assume that the decrease in battery energy is the same as that in a complete dispense, while there is no decrease in the refill volume. When the batteries are depleted, no dispense will occur regardless of the liquid inventory status. The dynamics of $L(t)$ and $E(t)$ will be further complicated by the implementation of battery replacement and refill maintenance policies. Solving the above equations, if not impossible, poses a considerable challenge. This is exacerbated by the necessity to solve them for hundreds or even thousands of dispensers, each subject to a distinct stochastic user arrival process. In such a complex scenario, discrete-event simulation emerges as an ideal tool. This method can effectively capture the complexity and uncertainty of real-world systems, and incorporate randomness, variability, dependencies, and interactions among system components ([Banks et al., 2009](#)).

Among the seven devices in this study, 6 of them are considered as traditional dispensers, which have a single power supply, which is a battery pack inside of the dispenser. One device (Device 6 in [Table 2](#)) employs the *Energy-On-the-Refill (EOR)* design and has two separate power sources, an AA alkaline battery embedded in the refill bottle, which is the so-called EOR, and a pack of four AA alkaline batteries within the dispenser housing, which is the auxiliary power supply (APS).

The EOR energy design ensures that the major power supply is replenished every time a new refill bottle is loaded into the dispenser. In such a setting, a dispenser’s EOR serves as the primary power supply until its depletion, then its APS takes over. Our simulation model will capture these features in the EOR model.

Most coefficients in the ordinary differential equation system (1) and (2) are determined by measuring the various dispensers in the delivery system engineering electronics test lab at GOJO Industries ([Table 2](#)). Besides, the effect of aging on alkaline batteries has been estimated to be a loss of 2–3 % of the total capacity per year ([Buchmann, 2001](#)). We notice that traditional dispensers are more susceptible to battery aging than the EOR design. This is because the main battery of an EOR dispenser is renewed at each refill replacement, while in a traditional dispenser, the same batteries are used until depletion. We decide to use 2 % as the yearly aging rate for all dispensers (hence, $e_s = 2\%$ /number of seconds in a year) because it slightly favors the traditional dispenser, and we want to show that the EOR design still outperforms. In [Littau et al. \(2013\)](#), similar power consumption data has been utilized to develop a mathematical model to estimate dispenser battery life over time.

3.2.2. The usage patterns

Statistical analysis has been conducted to study the usage pattern of the dispensers in four hospitals and develop an input (traffic) model for simulation. As illustrated in [Table 1](#), the usage data contains up to 30 million dispensing events from touch-free ABHR dispensers in various hospitals. It is important to acknowledge that the actual number of dispensers used at each facility might surpass the reported figure, as only a subset of dispensers is connected to the AHHMS monitoring system.

Our analyses of the usage data indicate that the usage patterns are nonstationary. Fluctuations in usage are observed across various time scales, including hours, days, weeks, and months. However, the most significant variability in time occurs at the hourly level. This observation aligns with findings from ([Boyce et al., 2019](#)), which analyzes a similar dataset in healthcare settings and points out that “the biggest fluctuations in median HH rates are across hours in a day, not across days in a

week or months in a year". Consequently, we model user arrivals at a dispenser as a nonstationary Poisson process with hourly arrival rates. The rate at each hour is calculated by first aggregating the total usage during that hour and then averaging it over the total number of days. Using this approach, each dispenser is associated with a vector in 24 dimensions, representing the average hourly rates for each of the 24 h in a day.

As shown in Table 1, the number of dispensers in a hospital is in the hundreds to thousands. To obtain generalized results that facilitate decision-making for the stakeholders, we utilize clustering analysis to identify a few representative profiles of usage patterns. The procedure takes two steps, prescreening and dedicated clustering.

In the prescreening step, we observe that nearly half of the dispensers in each hospital have few dispenses per day. We classify those dispensers as minimal usage dispensers. To obtain the minimal usage profile, we pool the usage patterns from all four hospitals and calculate the average below the median. Usage patterns that are above the median are used for the dedicated clustering.

In the dedicated clustering step, we employ the Gaussian mixture model (GMM) to cluster the non-minimal usage patterns. GMMs are commonly used as a parametric model to estimate the probability density of the representative clusters of high dimensional data (Peel and MacLahlan, 2000). The model assumes $p(x)$, the distribution of n independent and identically distributed samples $x = \{x_1, x_2, \dots, x_n\}$ can be represented by a finite mixture of Gaussian (normal) distributions:

$$p(x) = \sum_{k=1}^C \pi_k N(x|\mu_k, \Sigma_k)$$

where C is the size of the multivariate Gaussian distributions, $N(x|\mu_k, \Sigma_k)$ is the k -th component with vector mean μ_k and covariance matrix Σ_k ; and π_k is the corresponding mixing weight.

We use the package mclust (Scrucca et al., 2016 version 5.4.10) in R to perform the GMM classification and inside the package, the expectation-maximization (EM) algorithm is used to train the GMM models. The optimal number of the clusters and their geometry can be identified using the Bayesian information criterion or BIC (Fraley & Raftery, 1998; Schwarz, 1978):

$$BIC = \log(L) - m \log(n)$$

where $\log(L)$ is the log-likelihood for the model, n is the sample size, and m is the number of estimated parameters.

The two-step procedure has resulted in four usage profiles, which are named respectively "minimal", "low", "moderate", and "high" according to the intensity of the arrival rates. The resulting usage patterns are then used as the arrival rates of the nonstationary Poisson processes in our Arena simulation models.

3.2.3. Maintenance policies

We consider two refill maintenance policies 1) regular manual checks and replacement, and 2) real-time monitoring and replacement in advance. The first approach, which is widely adopted, involves determining when to replenish and estimating the duration of the replenishment process. We assume a 12-hour inspection interval for the refill, and replacement is immediate once an empty bottle is identified. In practice, housekeeping personals will periodically visit each location at scheduled intervals to inspect and refill the dispensers as needed. To determine this interval, GOJO conducts a survey on the inspection frequency for refills in the hospitals under study. Due to privacy concerns, the data is not shared with us. However, we are informed that the best scenario is that refills are checked every 12 h. This practice is implemented in ICU, where maintaining the highest hand hygiene standards for health care workers and visitors is critical. In other units, the inspection frequency may be significantly lower. We have set a 12-hour refill inspection interval in the simulation for the manual checks,

which allows us to compare the best-case scenario of the traditional approach with the more advanced approach.

The second approach employs the Internet of Things (IoT), utilizing smart devices connected to the dispensing system for real-time monitoring, data collection, and provision of recommendations or alerts to ensure the system's effective operation. For instance, IoT is applied to implement service alerts for refill monitoring. When a dispenser's refill level falls below a specified threshold, an alert is generated and sent to notify the maintenance personnels that a refill replacement is needed. While alerts can be triggered instantly, still there is a delay (lead time) between alerts and the refill replacement, which could take up to 12 h (assuming being taken care within the same shift). We set the delay time as 12 h in the simulation, aiming to compare the best-case scenario of the traditional approach with the worst-case scenario with service alerts.

Regarding battery replacement, we assume that the lead time (i.e., the duration to replace dead batteries) is a random variable with a discrete probability distribution. The distribution for battery maintenance lead time is determined based on a survey involving 74 acute care environment services employees across various healthcare facilities (refer to Table 3).

In both the refill and battery maintenance, it is possible to formulate an optimization problem to determine the optimal inspection intervals. We expect that distinct devices and various usage profiles will yield different optimal inspection intervals. For instance, the time it takes for a dispenser to deplete its ABHR depends on factors like its initial capacity, per dispense volume, and usage intensity. Consequently, the optimal solutions are likely to be device and usage pattern specific. However, such optimization is beyond the scope of our study. In our simulation model, we establish the inspection interval based on practical usage, guided by expert opinions. Our primary focus is on comparing the design impact of different devices.

3.2.4. The discrete-event simulation model

Discrete-event simulation models are developed by integrating the three components described above. Our model consists of three interdependent parts that capture the dispensing, refill maintenance, and battery replacement process respectively. These components share the same set of global variables to keep track of the remaining ABHR level and battery energy level(s). ABHR demand traffic is generated according to the non-stationary arrival profiles defined earlier, which triggers the consumption of ABHR and battery energy.

Fig. 1 depicts the operational logic of the two different dispensers and the maintenance for batteries and refills. The flowchart in Fig. 1(a) illustrates the traditional approach employed by Devices 1–5 and 7, where the dispenser relies on a single source of power supply built into the dispenser housing to operate. Fig. 1(b) displays a flowchart of the Energy-On-the-Refill design utilized by Device 6. Fig. 1(c) illustrates the operation of battery maintenance while Fig. 1(d) shows the housekeeping process of checking and changing ABHR refills.

In a typical simulation run, users are initially generated as entities based on a predefined usage profile, characterized by a non-stationary Poisson process with specified hourly arrival rates. Upon arrival, a user will initiate a dispense event by attempting to use the dispenser. The outcome of this dispense event depends on the current energy and liquid inventory status of the dispenser ($E(t), L(t)$), resulting in either a

Table 3
Lead time of battery maintenance.

Lead Time	Frequency	Percentage
Within 12 h	10	14 %
Within 16 h	36	49 %
Within 24 h	17	22 %
Within 32 h	5	7 %
Within 48 h	5	7 %
More than 48 h	1	1 %

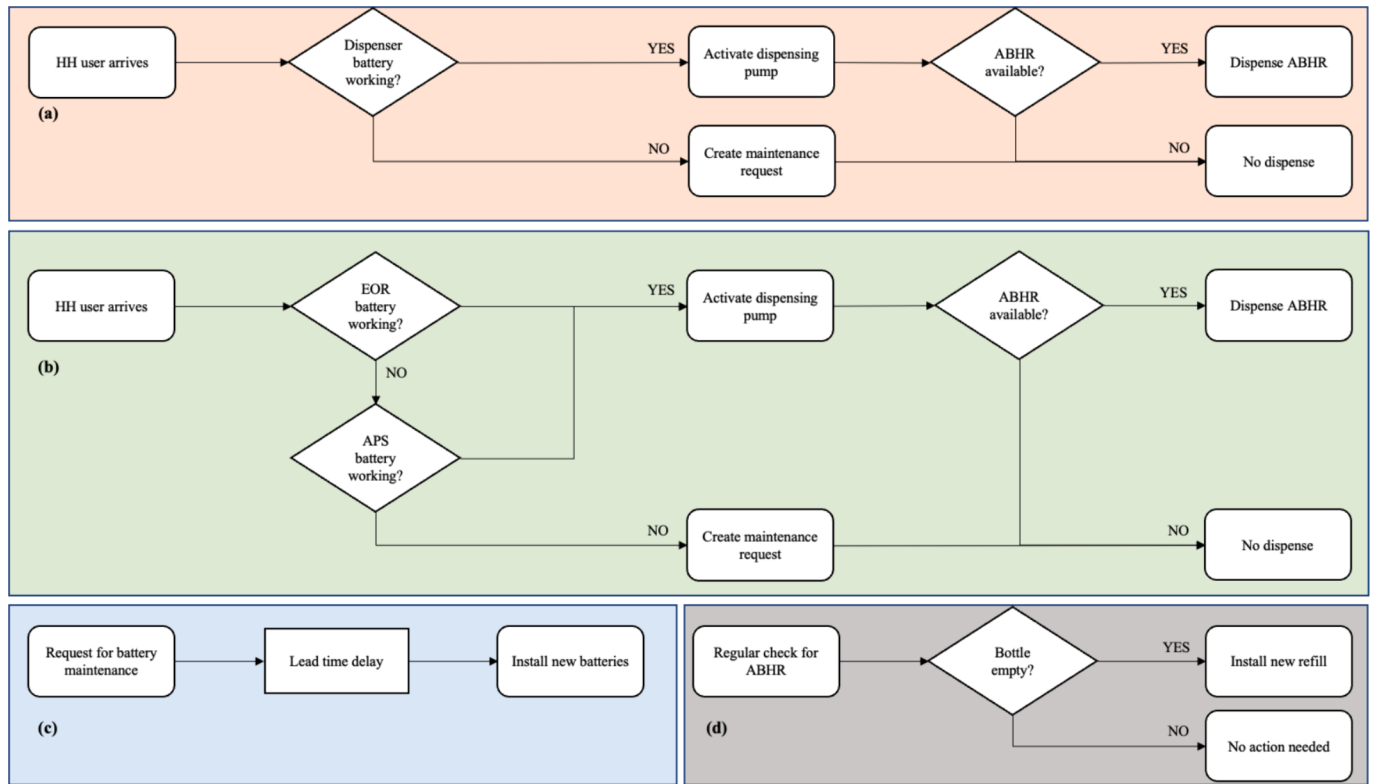


Fig. 1. Flowcharts of the simulation model of (a) dispense model for traditional design; (b) dispense model for EOR design; (c) battery maintenance and (d) ABHR refill maintenance.

successful dispense or a failure (which could manifest as an “empty” dispense or no dispense at all). Regardless of the outcome, users leave immediately after their dispense attempt. Meanwhile, regular refill status checks are conducted by housekeepers every 12 h. If the refill level falls below 5 mL,² the refill is considered empty and promptly replaced with a new bottle. Requests for battery maintenance are assumed to be automatically generated when a dispenser’s batteries are dead, with the lead time for replacement drawn from a discrete probability distribution introduced earlier. We run simulations for the seven devices, using four distinct clustered arrival profiles with varying total arrivals within a day. The simulation run spans a duration of 6 years (2160 days), reflecting a typical lifespan for automated ABHR dispensers. To assess the reliability of each dispenser type under a specific arrival profile, we record HH misses separately for cases involving dead batteries and those due to ABHR depletion. Each scenario, comprising a device type and an arrival profile, is simulated for 25 replications.

3.3. Verification and validation

Verification and validation help determine the correctness and accuracy of simulation models. More specifically, verification ensures a model’s developing and implementation are correct and validation checks if the model’s output is consistent with the actual system within an acceptable range of accuracy (Banks et al., 2009). Both verification and validation are performed using procedures suggested by Sargent, (2020) throughout the model development process.

3.3.1. Conceptual model validation

The conceptual model of both the traditional dispensers and EOR

dispensers are verified with the hardware engineers and product managers of GOJO through multiple meetings and discussions. In a field trip to the company’s electrical testing laboratory, GOJO’s engineers explain the designs and working mechanisms of both types of automatic dispensers and provide actual devices for the modelers to study. The model developers present flow diagrams of the models and associated math equations on battery and refill level evolutions for close examination. Assumptions on the maintenance policies of batteries and refills are also discussed and verified during these meetings.

3.3.2. Computerized model verification

We also verify that the implementation of the conceptual model is correct, and the models is executed properly. The computerized models are run in Arena with dynamic animations of the battery level and refill level in front of the collaborators of GOJO. Sensitivity analyses are performed to access the robustness of the models. We vary usage patterns, refill capacities of the dispensers during simulation, and discuss with GOJO engineers whether the changes in the output parameters are consistent with the behavior of actual automatic sanitizer dispensers.

3.3.3. Operational validation

Validation is more difficult, mostly due to the lack of output data from the real system. For example, the Automated Hand Hygiene Monitoring System (AHHMS) installed in the hospitals could not detect nor record hand hygiene misses, the output metric that we are interested in. AHHMS only records the attempts to use a dispenser, and it does not differentiate successful dispenses from hand hygiene misses, let alone whether a failure is caused by dead batteries or empty refills. Nevertheless, we manage to validate our model on the average number of sanitizer refills per dispenser each year. Based on information provided by GOJO, a single sanitizer dispenser consumes around five bottles of refill in a year on average in hospital 3. Our validation test focuses on comparing the system response, namely, the observed average number of sanitizer refills at hospital 3 with $\mu_0 = 5$ bottles to the model response

² Due to air pressure and sanitizer sticking to the inner surface of a refill bottle, a dispense residual exists. 5 mL was recommended by field experts as a generalized estimate for the dispensers in this study.

Y_3 . Formally, a statistical test of the null hypothesis:

$$\begin{aligned} H_0 : E(Y_3) &= 5 \text{ bottles.} \\ \text{versus.} \\ H_1 : E(Y_3) &\neq 5 \text{ bottles.} \end{aligned}$$

is conducted at the significance level $\alpha = 0.05$. In order to determine the sample size n , a power analysis for a one-sample, two-sided t -test (Banks et al., 2009; Hines et al., 2008) is first carried out with targeted power $1 - \beta = 0.90$ and difference threshold 1 bottle. That is, we would like to control the false negative rate β to be less than 0.10, hence the null H_0 (model validity) will be rejected with probability at least 0.90 if the true mean number of refills of the model, $E(Y_3)$, differed from $\mu_0 = 5$ bottles by 1 bottle. Our initial pilot run indicates that the standard deviation of Y_3 is $S = 0.6845$, which yields:

$$\hat{\delta} = \frac{|E(Y_3) - \mu_0|}{S} = \frac{1}{0.6845} = 1.461$$

Based on the Operating-characteristic (OC) curves (Table A.10 in Banks et al., 2009), we have chosen a sample size $n = 5$ so that $\beta(\hat{\delta}) \leq 0.10$. By collecting the corresponding output values from simulation with $n = 5$ replications, we have derived the test statistics $t_0 = 0.936$. Since $t_0 = 0.936 < t_{0.025,4} = 2.78$, we conclude that we do not have sufficient evidence to say that the simulation model is invalid. This also corresponds to a 95 % confidence interval for average number of refills per year as [4.437, 6.136]. Since the historical average number of refills, five bottles per year, falls into the confidence interval, we are 95 % confident that the model output is consistent with the reality. The comparison of output behaviors between the simulation model and the actual system is also shown in Fig. 2.

4. Results

4.1. Usage profiles

The usage profiles are trained on the pooled data from the four hospitals. Using the two-step procedure, we derive four distinct usage profiles: “minimal”, “low”, “moderate”, and “high”, based on arrival rate

intensity. The “minimal” cluster is identified during the prescreening process, while the other three clusters are determined using Gaussian mixture models. Fig. 3 shows the Bayesian Information Criterion (BIC) plot fitted to the “non-minimal” pooled usage data. In the mclust package, 14 possible models with different geometric characteristics are specified with three-letter identifiers, such as EII and EVV. The BIC scores are presented as a function of the number of components. The VEE model with seven components maximizes BIC at 27333.08 and is selected by default. However, to simplify simulation and explanation, we specify three components to obtain a smaller number of clusters. The BIC for VEE with three components is 25678.88, which is nearly optimal. The resulting clusters are labeled “low”, “moderate”, and

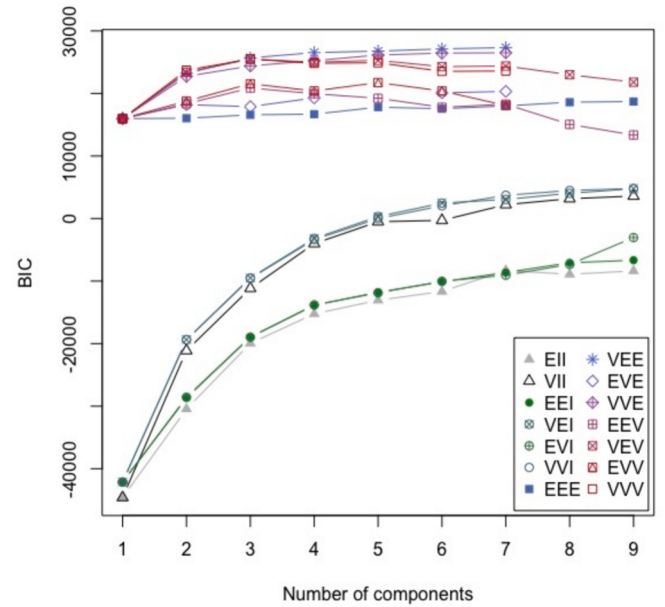


Fig. 3. BIC scores for GMM models with various component sizes and cluster geometries.

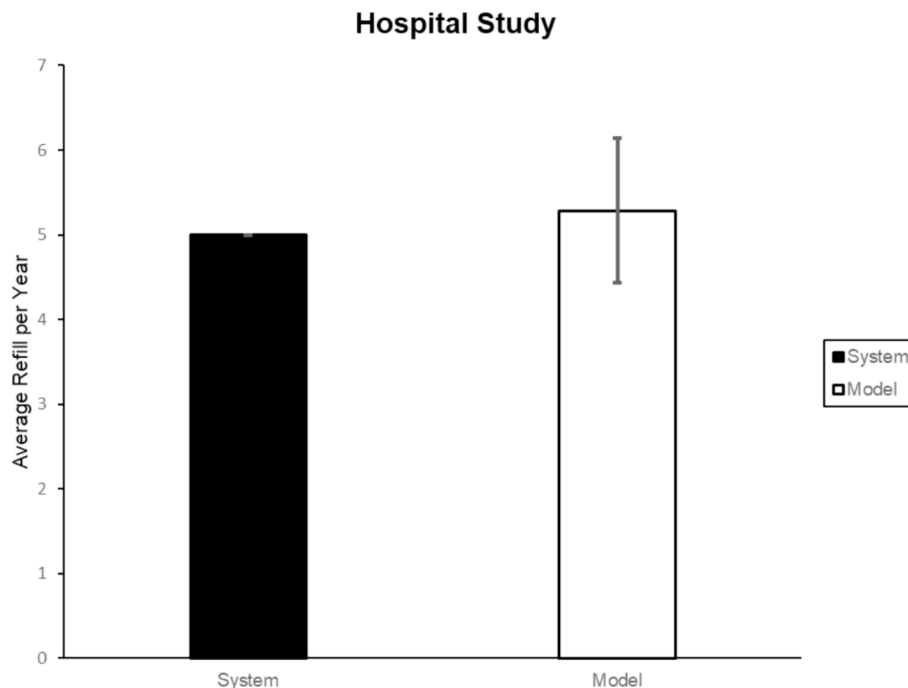


Fig. 2. Average Refill per Year in hospital 3.

“high” based on the average daily usage they represent.

Fig. 4 depicts the hourly usage rates of a dispenser under the four profiles. It is noteworthy that these profiles exhibit similar fluctuations throughout a day, with peak usage hours typically observed in the morning, around 7–9 am, and off-peak hours occurring around midnight. When summing up the hourly rates over a day, the average daily usages for the four profiles are 3.81, 13.38, 38.31, and 56.71, respectively.

Table 4³ presents the number of dispensers belonging to each cluster/profile based on the clustering analysis. The proportions of the profiles at each hospital are illustrated in Fig. 5. It is evident that the four hospitals exhibit both differences and similarities in their dispenser usage patterns. Significant variations are observed in the percentage of dispensers categorized under the high usage profile. For example, only 0.4 % of dispensers in hospital 3 are characterized as having a high usage pattern, while 21.8 % of dispensers in hospital 2 demonstrate high usage. These disparities can be attributed to the differences in hospital types, dispenser quantities, and locations. Across all four hospitals, the “minimal” profile takes up approximately 50 % of the dispensers, indicating that nearly half of the monitored dispensers in the hospitals are rarely used.

4.2. Hand hygiene misses due to dead batteries

We categorize hand hygiene misses into two groups, *HH misses due to dead batteries*, and *HH misses due to ABHR depletion*. The former measures the energy efficiency of a dispenser, while the latter reflects the efficiency of a refill maintenance schedule.

Fig. 6 illustrates the resulting HH misses due to dead batteries for one dispenser over six years of operation under the four usage patterns estimated by our simulation model. Observe that under minimal or low usage profiles, most dispensers generate very few HH misses. However, HH misses become more substantial under moderate and high usage profiles. Among the seven devices, Device 1 and Device 6 stand out, showing no hand hygiene misses caused by dead batteries in six years under all usage patterns, while Device 2 generates the most HH misses due to dead batteries. The reasons are straightforward. Device 1's

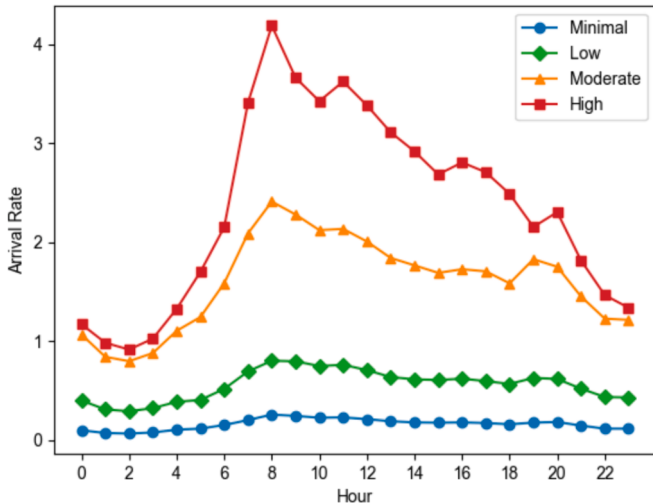


Fig. 4. Usage patterns of a dispenser over 24 h derived via the GMM clustering method.

³ Note that the sum of the dispensers from hospitals 2 and 3 in Table 4 are slightly less than those shown in Table 1, because a few dispensers have incomplete data thus cannot be classified.

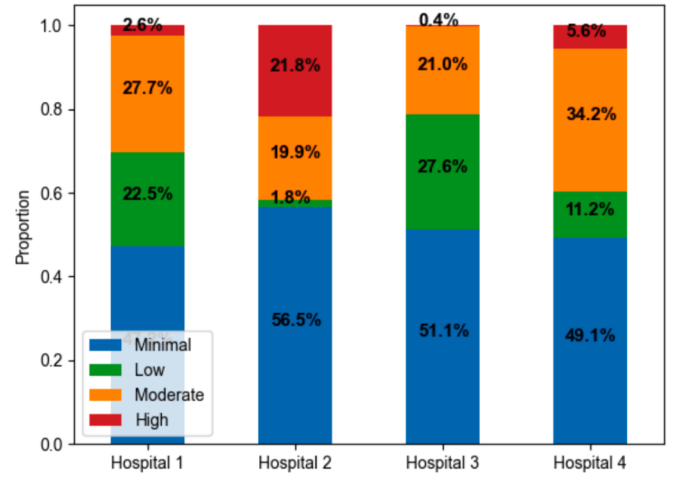


Fig. 5. Proportions of clustered profiles in each hospital.

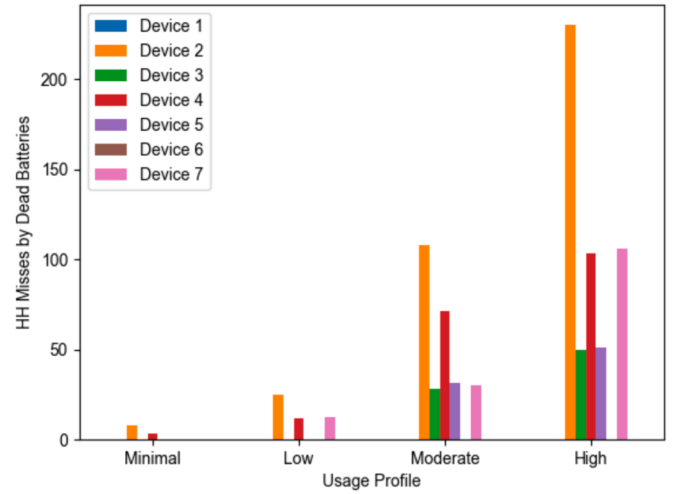


Fig. 6. HH misses due to dead batteries.

exceptional performance is attributed to its highly efficient energy design, particularly its low energy consumption in dispensing and idling. For Device 6, its unique EOR (Energy On the Refill) design ensures that the battery is replenished each time a new refill is added.

During the simulation, we observe that there is consistently ample energy remaining in the EOR battery when the refill bottle is replaced. Furthermore, even if the EOR battery is depleted, the auxiliary battery will seamlessly activate to power the system.

4.3. Hand hygiene misses due to ABHR depletion

When the refill is depleted, users will experience an empty dispense if a dispenser still has sufficient power supply. This event is referred to as a HH miss due to ABHR depletion. Through simulation, our aim is to compare HH misses under the traditional maintenance approach with those under the real-time service alert approach.

In the traditional approach, the refill bottle is manually checked every 12 h, and it is replaced immediately once found empty. In the service alert approach, the dispenser is connected to a real-time monitoring system, and a service alert (e.g., text message) is sent to the housekeeping team once the ABHR volume falls below a prespecified threshold. In comparing the two maintenance approaches, the threshold is set at 5 % of the full capacity. Later in Section 4.5, we further explore the tradeoff between fewer HH misses and more ABHR liquid waste by

varying this threshold.

Fig. 7 demonstrates HH misses due to ABHR depletion in a six-year operation estimated by our model. Devices 1–7 are all maintained under the traditional manual-check approach, while Device 8 adopts the real-time monitoring approach. In fact, Device 8 is identical to Device 7 but enhanced with service alert technology from its manufacturer.

From Fig. 7, it is evident that under minimal and low usage patterns, very few HH misses occurred across all device types, and the traditional maintenance policy (checking every 12 h) is sufficient to maintain good performance. However, when the usage pattern shifts to moderate and high, all dispensers (Devices 1–7) under the traditional manual check maintenance policy begin to generate a significant amount of HH misses due to ABHR depletion. The number of HH misses due to ABHR depletion appears to be inversely proportional to the capacity of the dispenser. For instance, Device 4 exhibits the lowest HH misses among all dispensers because it has the largest refill capacity and the smallest dispense volume.

In the high usage scenario, a notable 81.6 % reduction in HH misses is observed when comparing Device 7 and Device 8. Furthermore, Device 8 achieves the lowest hand hygiene misses among all device types in various arrival profiles. The introduction of the refill service alert has made Device 7 the most robust dispenser in terms of HH misses due to ABHR depletion.

4.4. Hospital-scale performance comparison

After obtaining the performance metrics for a single dispenser, we extend the results to hospital scales by multiplying the performance metrics of a single dispenser by its quantity in the hospital. The number of dispensers under each usage profile at the four hospitals is provided in Table 4. As mentioned before, not all dispensers are connected to the AHMS monitoring system, the source of the data for analysis and simulation. Even though we do not have information about the unmonitored dispensers in the hospitals, we are informed that these monitored dispensers can represent the majority of the hospital-level operation, so we simply use them in the comparison. Fig. 8 summarizes the simulated hand hygiene performance in each hospital. The performance metrics of interest include total HH misses due to dead batteries, total HH misses due to ABHR depletion, total dispenser downtime due to dead batteries, and the number of battery packs used over six years of operation.

Fig. 8(a) shows the total HH misses due to dead batteries in each hospital. Notably, Device 2 generates the highest number of HH misses, followed by Device 4. In contrast, Device 1 and Device 6 achieve 0 HH misses over six years of operation.

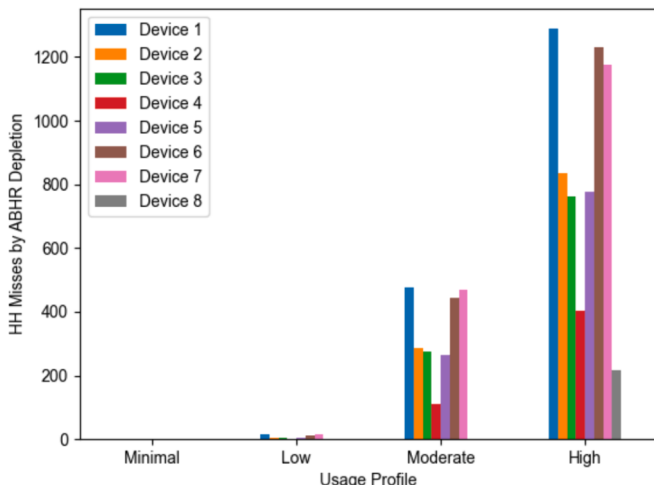


Fig. 7. HH misses due to ABHR depletion.

Table 4

Number of ABHR dispensers from each usage profile.

	Hospital 1	Hospital 2	Hospital 3	Hospital 4
Minimal	323	153	139	79
Low	154	5	75	18
Moderate	190	54	57	55
High	18	59	1	9

Fig. 8(b) shows the total HH misses due to ABHR depletion in each hospital, where Device 1–7 implement the traditional refill maintenance policy, and Device 8 is Device 7 equipped with the refill service alert. Under the traditional maintenance policy, Device 4 has the lowest HH misses at each hospital, primarily due to its relatively low dispense volume per actuation. The results show that the HH misses for Device 7 reduce significantly, moving from the second highest to the lowest after implementing the refill service alert (as in Device 8). While the total number of ABHR dispensers and the proportions of dispensers per usage profile may differ in each hospital, the results at the hospital level align with the single dispenser results provided in Fig. 7. Moreover, by comparing Fig. 8(a) and 8(b), it can be concluded that the major cause of hand hygiene disruption is ABHR depletion.

In Fig. 8(c), we compare the dispenser's cumulative downtime hours caused by battery failures in each hospital. It is unsurprising to observe that the cumulative downtime shares the same pattern as that of HH misses due to dead batteries in Fig. 8(a).

Fig. 8(d) shows the total number of battery change-out events that would occur during a six-year simulation if a hospital were to exclusively adopt a specific dispenser. Device 2 receives the highest number of battery maintenance events, while Device 1 and Device 6 have the lowest in each hospital. Additionally, it is noteworthy that a dispenser's ranking of battery change-out events is consistent with the HH misses and downtime due to dead batteries.

4.5. Trade-off between hand hygiene misses and ABHR waste

In our simulation model, a tunable parameter is the refill alert threshold. This threshold determines the ABHR volume at which the maintenance team should be alerted to perform a refill replacement. The choice of the threshold value inherently involves a trade-off between HH misses due to ABHR depletion and the volume of sanitizer discarded due to preventive maintenance. Simply put, setting a conservative threshold that triggers service alerts when the refill is still ample reduces hand hygiene misses but increases sanitizer waste.

Fig. 9 illustrates the trade-offs on Device 7 under “minimal”, “low”, “moderate”, and “high” usage intensity. We set the thresholds to 1 %, 2 %, 4 %, 6 %, and 8 % of Device 7's full refill capacity and run simulations for the four different usage profiles. It is notable that the “sweet spot” in the trade-off varies across different profiles. As depicted in Fig. 9, the “valley” that results in acceptably low HH misses and low ABHR wastage occurs at different thresholds depending on the usage intensity. When the usage profile is minimal or low, 2 % seems a good choice for the ABHR threshold. Under moderate and high usage, raising the alert when the refill level is below 4 % tends to be better. It is important to note that in such considerations, we prioritize HH misses slightly more than ABHR wastage.

5. Discussion

In this study, we estimate the performance of automatic hand sanitizer dispenser with different designs and maintenance policies in hospitals. This is useful for choosing proper dispensers and maintenance schedules to optimize hand hygiene compliance in healthcare settings. The simulation results suggest that a dispenser's performance is highly affected by its energy design and the facility's maintenance policy. To reduce the hand hygiene misses, novel technologies such as Energy On

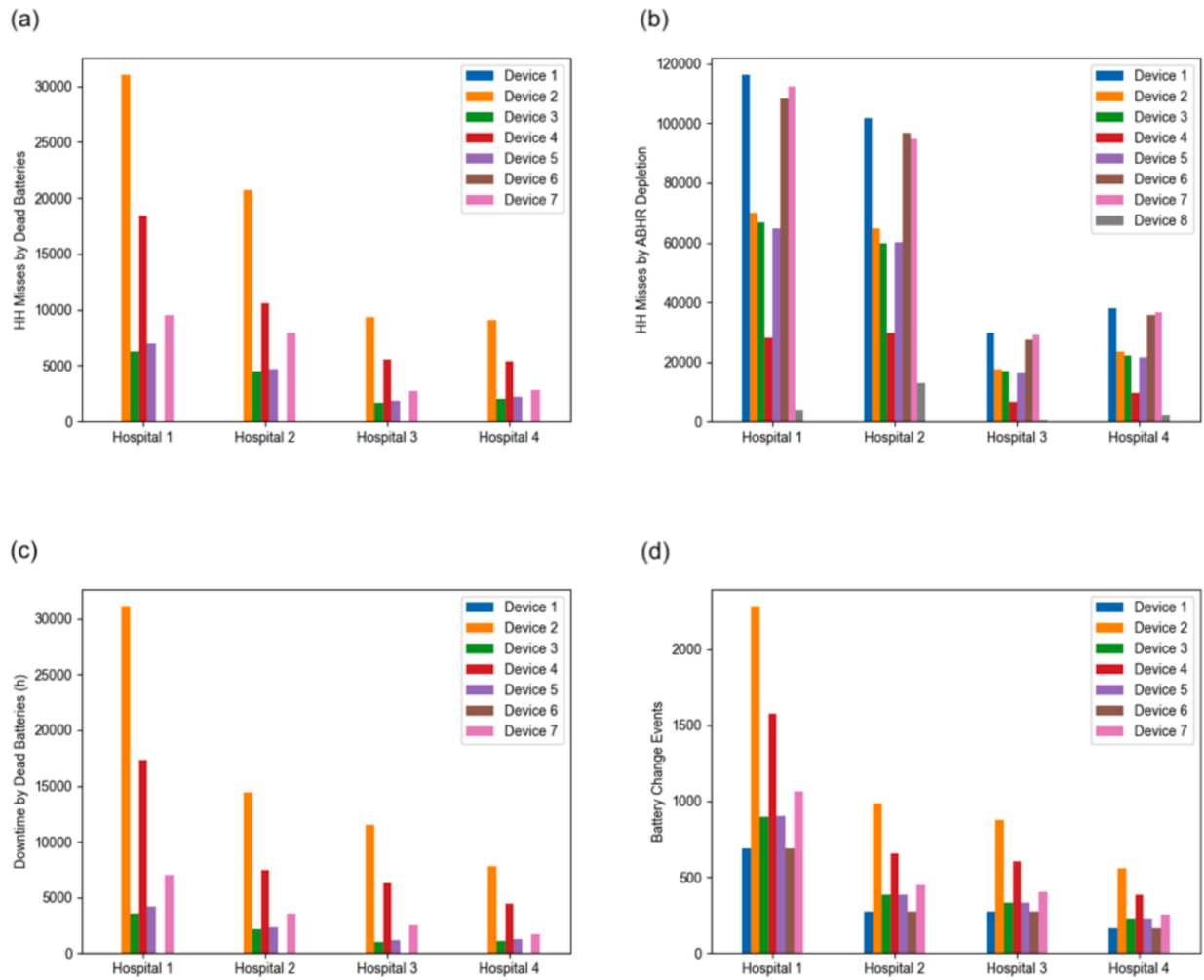


Fig. 8. Dispenser performance in each hospital.

the Refill and refill service alert are shown to be effective.

We also find that HH misses vary significantly under different usage patterns. In general, higher usage rates will result in more dispense events, leading to a faster depletion of ABHR in dispensers. Consequently, dispensers will experience more breakdowns, generating more HH misses in hospital locations with higher foot traffic (e.g., entrance, hallways), or with stricter HH compliance requirements for healthcare workers (e.g., ICU unit). Since high-usage areas are typically associated with more patients/visitors, inoperable dispensers in these areas could negatively impact the patient satisfaction scores of a hospital.

Our findings yield several implications for reducing HH misses and improving workflow efficiency in healthcare facilities. For traditional single-battery dispensers, a design with low dispense energy, low idle power, and large batteries is effective enough to mitigate downtime and HH misses caused by battery failures. However, the double-battery EOR configuration outperforms most traditional dispensers, suggesting its potential consideration as the next-generation automatic dispenser for better performance and less maintenance cost. To reduce HH misses due to ABHR depletion, we recommend implementing an add-on detection system with a refill service alert. If this is not an option due to the cost or other considerations, simply increasing inspections frequency would help. Our analyses also underscore the importance of analyzing foot traffic and usage patterns in potential locations before installing ABHR dispensers. Notably, our examination of usage data reveals that the current placement of ABHR dispensers in the four hospitals is suboptimal, with many dispensers in various locations experiencing very low usage even during the COVID-19 pandemic.

The limitations of this study center around assumptions that could impact the model accuracy. The aging of the systems is not accounted for, potentially affecting variables such as the amount of ABHR per dispense, the energy consumption, and the speed of dispense. Instead, we adopt a simplification for the battery energy consumed during dispensing and idling. In practice, a dispenser's energy consumption from the battery could be affected by numerous factors, including but not limited to, the number of dispenses, battery aging, operating temperature, and the duration between dispenses, especially in low-usage scenarios. To better capture the nonlinearity of battery drain, additional knowledge of the system and advanced modeling techniques are necessary. For instance, employing ordinary differential equation (ODE) models to describe electrochemical reaction dynamics within batteries could be beneficial. Additionally, one might consider applying data-driven machine learning to predict the remaining capacity of batteries (Ng et al., 2020). We leave this as a task for future investigation and development. One may also want to incorporate the total cost of ownership for each device, which can aid facility managers in making more informed decisions regarding the purchase and maintenance in the long run.

6. Conclusion

In this paper, we propose a data-driven DES framework to assess the hand hygiene performance of automatic ABHR dispensers in healthcare settings. We model seven different dispensers, conduct simulations using real-world data, and compare their long-term performance under

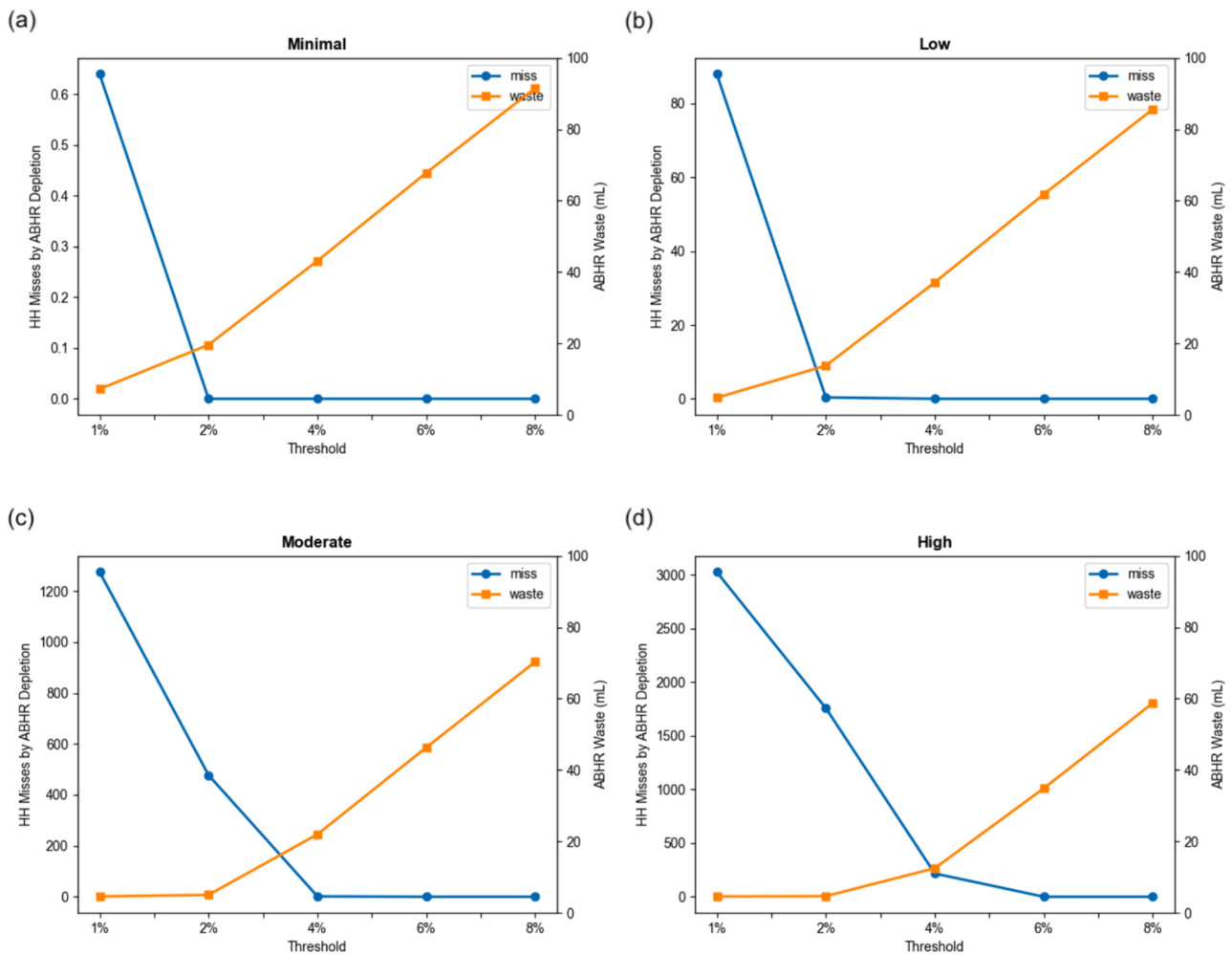


Fig. 9. Trade-offs between HH misses due to ABHR depletion and liquid waste by dispenser usage profile.

various maintenance policies. The results suggest that the energy design of a dispenser can significantly affect the number of hand hygiene misses it generates, and a facility's maintenance policies are crucial for mitigating workflow disruption caused by ABHR depletion and battery failures of the dispensers. Furthermore, novel technologies such as Energy On the Refill and refill service alert, which facilitate preventive maintenance of batteries and refills, prove highly effective in reducing hand hygiene misses.

In conclusion, our methodology, encompassing the analysis of dispenser usage data, building simulation models, interpreting results, and making recommendations, offers a convenient solution for evaluating the performance of automatic sanitizer dispensers under uncertain usage conditions. We have developed a generalizable and customizable approach to estimate the performance of automatic sanitizer dispensers, which can be applied across different dispenser types, environmental settings, and maintenance policies. The inherent trade-off between cost and performance always exists in optimizing a system's operation. While our approach provides a practical means to find such a balance, it is essential to remember that learning the optimal strategy for operating a complex system usually involves solving optimization problems with multiple objectives. The practical optimal solution depends on the expectations of how the system should function and the tolerance for the associated costs to maintain such performance.

Discrete-event simulation is an inherently cost-effective and time-saving approach that aids decision-making. When combined with clustering analysis on the usage data, we identify the representative usage profiles with high fidelity and easy interpretability, simplifying the

modeling and simulation process. The case study of automatic ABHR dispensers in hospitals demonstrates the benefit of this data-driven DES framework. The application of machine learning techniques to assist input modeling not only enhances the accuracy of parameter estimation but also expedites the simulation process. In the era of big data, leveraging machine learning and data analytics will make discrete-event simulation more efficient and powerful.

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CRediT authorship contribution statement

Nanshan Chen: Writing – original draft, Visualization, Software, Methodology, Formal analysis. **James W. Arbogast:** Writing – review & editing, Validation, Supervision, Conceptualization. **Demetrius Henry:** Resources, Investigation. **Theodore T. Allen:** Writing – review & editing, Methodology, Conceptualization. **Susan O'Hara:** Writing – review & editing, Validation. **Cathy H. Xia:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

[TTA and CHX had a sponsored research agreement with GOJO Industries Inc. DH is a full-time employee of GOJO. JWA was a full-time employee of GOJO when the work was done].

Data availability

The data that has been used is confidential.

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