Discussions of a Preliminary Hand Hygiene Compliance Monitoring Application-as-a-Service

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Abstract: Hospital Acquired Infections (HAIs) are a global concern as they impose significant economic consequences on the healthcare systems. In the U.S. alone, HAIs have cost hospitals an estimated $9.8 billion a year. An effective measure to reduce the spread of HAIs is for Health Care Workers (HCWs)to comply with recommended hand hygiene (HH) guidelines. Unfortunately, HH guideline compliance is currently poor, forcing hospitals to implement controls. The current standard for monitoring compliance is overt direct observation of hand sanitation of HCWs by trained observers, which can be time-consuming, costly, biased, and sporadic. Our research describes a hand hygiene compliance monitoring app, Hygiene Police (HyPo), that can be deployed as a service to alleviate the manual effort, reduce errors, and improve existing compliance monitoring practice. HyPo exploits machine learning analyses of handwashing compliance data from a 30-bed intensive care unit to predict future compliance characteristics. Based on the results, HyPo then provides HWCs with timely feedback and augments the current monitoring approach to improve compliance.

1 INTRODUCTION

Emerging concerns in healthcare. Hospital Acquired Infections (HAIs) are occupational infections acquired by Healthcare Workers (HCWs) or by patients in healthcare facilities that appear after patient discharge (WHO, 2009). HAIs represent significant health problems, with a considerable economic impact on patients and hospitals worldwide.

Persistent exposures to diseases and lack of appropriate hand hygiene (HH) practice can cause HCWs' hands to become carriers of infections transmitted to patients or other staff through physical contact. To reduce re-admission rates, therefore, HCWs are expected to comply with HH guidelines to prevent the spread of HAIs in healthcare facilities. The current standard practice of compliance monitoring is for covert human auditors to unobtrusively observe and record HH compliance of medical workers. Unfortunately, this approach is costly and subject to bias (Boyce et al., 2009) due to the Hawthorne effect (Eckmanns et al., 2006), which occurs when subjects of a study change their behavior due to awareness of being observed.

Contribution. Based on our preliminary study on HH compliance characteristics using machine learning (Zhang et al., 2016), this work proposes a hand hygiene compliance monitoring app, Hygiene Police (HyPo), that can be deployed as a service. The goal of this app is to mitigate the laborious effort and reduce errors of direct observation.

App workflow. HyPo is implemented as a Java-based desktop app that communicates to and from Bluetooth Low-Energy (BLE) devices equipped at the facility from our previous study (Zhang et al., 2016). The schematic in Figure 1 depicts the overall app workflow, which is divided into the following three stages (the last two are the core components of HyPo):

1. **Data Acquisition**, where raw data is acquired from the BLE devices.
2. **Data Mining**, where the raw data undergoes a data mining process provisioned by HyPo to produce a set of features that is fed to Feature Selection algorithms to obtain a Sanitized Dataset. The Feature Selection is done to improve the execution performance of the Machine Learning (ML) methods that will follow by determining the most relevant features and removing the others from the Sanitized Dataset.

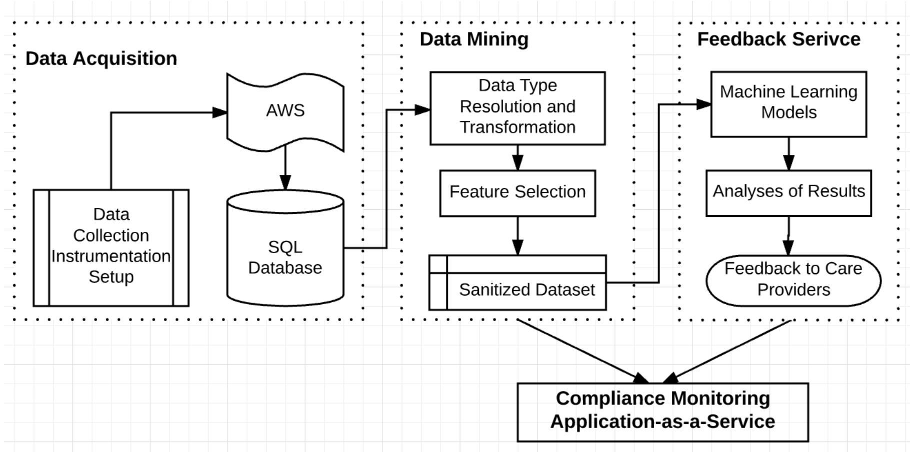

Figure 1: The Overall System Flow: from Data Collection to Post-prediction Analysis and Feedback Service.

3. **Feedback Service**, where the ML models are run over the Sanitized Dataset to produce feature set that can be used to provide timely feedback to healthcare providers.

Paper organization. The remainder of this paper is organized as follows: Section 2 defines key terms frequently referenced throughout the paper; Section 3 describes the data collection setup; Section 4 details the data preparation and mining process; Section 5 describes Hypo's feedback service and how it complements the direct observation approach; Section 6 surveys and compares existing research in the area of hand hygiene compliance monitoring applications; and Section 7 presents concluding remarks and outlines future extensions of this work.

2 HAND HYGIENE COMPLIANCE OVERVIEW

This section defines the following terms that are used frequently in the paper:

1. **Hand hygiene opportunity**: an opportunity for hand cleaning is presented before each care provider's entry/exit of a patient room.
2. **Hand hygiene/handwashing compliance**: each hand hygiene opportunity requires one hand hygiene action, which should be a corresponding positive (compliance) or negative (non-compliance) action (EFORE, 2009).
3. **Entry compliance**: hand hygiene compliance observed at staff's entry to a patient room, determined by *wash on entry*.
4. **Exit compliance**: hand hygiene compliance observed at staff's exit from a patient room, determined by *wash on exit*.
5. **Wash on entry**: hand hygiene action at patient room entry that determines entry compliance, true if performed and false otherwise.
6. **Wash on exit**: hand hygiene action at patient room exit that determines exit compliance, true if performed and false otherwise.

Our previous study collected 60 days of care providers' real-time location and handwashing data, from an intensive care unit (ICU) equipped with 30 beds, and observed two major correlating factors to compliance: (1) entry compliance has an 89% accuracy on predicting exit compliance and (2) exit compliance can predict entry compliance at the next visit (for the same staff) at an accuracy as high as 77%. Likewise, location data was observed to have a minor impact on predicting exit compliance (Zhang et al., 2016).

Based on this previous study, in the HyPo app we compiled the following rules of hand hygiene compliance that ICU staff should abide by:

1. All on-duty staff at the ICU were required to wear a BLE badge.
2. All staff were required to sanitize their hands within a short interval of 2 minutes upon entering a patient room and before exiting the same room.
3. Each compliant action should be associated with an activation of a specific soap dispenser with disinfectant solution against Clostridium difficile, a common HAI spread through physical contact (Shrestha et al., 2016). These dispensers are located both inside and outside each patient room.

These rules only apply to this ICU but can be configured to work with other caregiving settings. The rest of this paper describes the application of HyPo using the same device-equipped 30-bed ICU from our previous study (Zhang et al., 2016) as an example.

3 DATA ACQUISITION

This section describes the data acquisition process, where real-time location data and handwashing station activation data is recorded, and then provides an overview of the essential data fields extracted from the collection. The process described in this section is one approach of obtaining the hand hygiene compliance data to provide input for our app, but it is by no means the only option to acquire this type of data.

3.1 Instrumentation Configurations

The ICU with HyPo deployment was equipped with a Bluetooth Low-Energy (BLE) indoor positioning system that provides room-level accuracy for reporting staff locations in real-time. The system produced the location data for all staff with BLE badges.

The ICU also deployed Gojo Active Monitoring handwashing stations, which record each dispenser activation. These activation events were then combined with real-time location data to track individual staff handwashing compliance. The system expected to receive at least one handwashing event from either a sanitation station inside of the room or a station immediately outside the room within two minutes prior to entry, abiding the facility rules described in Section 2. Similarly, two minutes before or after room exit, the system expected one handwashing event from either sanitation stations.

Overall, the dataset collected at the studied ICU contains 8 weeks of events recording activities from 180+ soap dispensers activated by 60 badged nurses 24 hours a day. All raw event data was streamed to a data storage on Amazon Web Services (AWS), which was post processed and output to a SQL database. We then extrapolated the data fields of interest for compliance predictions and analyses.

3.2 Dataset Limitations

Although real-time location data was acquired and handwashing station activations recorded at the ICU, the dataset was still an estimate rather than a ground truth of hand hygiene compliance. The dataset collected has a number of key threats to validity, including: (1) not all staff wore their BLE badges at all times, (2) the system could not differentiate activations from badged vs. non-badged visitors/staff, and (3) subsets of the monitoring equipment went offline at some intervals and prevented data capture in certain rooms.

However, we did not consider these limitations as fatal to our study results because we could either easily eliminate the data entries associated with these threats or discard the marginal impact that the threats had on our findings.

3.3 Dataset Schema

From the SQL database we obtained an initial dataset by omitting certain data fields with extraneous information, such as device IDs of the wearable badges, internally-used identifiers of the patient rooms, etc. The data fields associated to each patient room visit event that we deemed essential thus extracted from the database include:

1. *Staff ID* - ID of badge worn by the staff who has been associated with a patient room visit
2. *Location* - patient room number visited by the badged staff
3. *Entry time* - timestamp (in CDT) at which the badged nurse entered the patient room
4. *Exit time* - timestamp (in CDT) at which the badged nurse exited the patient room
5. *Wash on entry* - a boolean value indicating whether the staff properly performed hand hygiene on patient room entry
6. *Wash on exit* - a boolean value indicating if the staff properly performed handwashing on patient room exit
7. *Duration* - for how long (in milliseconds) the staff was in the patient room

4 DATA PREPARATION

This section discusses how we prepared the collected data to maximize the utilization of our machine learning classifiers, which is an important capability offered by HyPo. This process is the same as that employed in (Zhang et al., 2016) to assist the analyses and characterization of hand hygiene compliance. Other influencing factors of hand hygiene compliance may be discovered as more relevant data becomes available, such as patient admittance details, medical records of admitted patients, facility regulations of compliance, etc.

Despite the specificity of the dataset used throughout this paper, the data mining process provided by

HyPo as described below can be generalized to support transformations of different forms of data collected in other facilities.

4.1 Data Transformation

Most machine learning (ML) classifiers yield better results when the input dataset is structured in certain ways. For example, suppose we want to know if the day of week (Monday to Sunday) influences compliance, some ML classifiers will yield better results if we express date as a set of integers ranging from 1 to 7, as opposed to a real continuous stream of timestamps expressed in milliseconds.

As another example, our location data consists of room numbers, which provides little information regarding spatial distribution of the rooms. If we want to know whether compliance decreases in nearby locations, we must first transform the room numbers into coordinates on the facility's floor plan, for instance.

To obtain a transformed schema that can be better handled by our classifiers, we took the collected dataset and performed the following transformations over it:

1. We converted all event data from the original timestamp format into an integer field with range 1 to 7 to represent day of week, an integer field with range 1 to 4 to represent time of day in morning, afternoon, evening, bedtime, and another integer data field of 0-23 to represent hour of day. The numeric representations of the original nominal time stamp data will allow our classifiers to achieve higher classification accuracy.
2. We mapped each patient room on the ICU floor plan to a set of x and y coordinates to identify the spacial location. We then extended each entry in the dataset to include these corresponding coordinates of the patient room.
3. For each data point we added new fields to include the previous record of the corresponding badged staff's handwashing data, *i.e.*, duration, location, washed on entry, and washed on exit. To ensure data integrity, we removed all entries that did not have previous handwashing records.

As a result of these transformations, we obtained a new schema consisting of a minimal set of features that our application expects to receive for best accuracy:

1. staff ID - integer
2. location (room number) - integer
3. washed on entry - TRUE/FALSE
4. washed on exit - TRUE/FALSE
5. duration (s) - length of patient room visit in seconds, integer
6. entry hour - hour of day on room entry, 0-23
7. exit hour - hour of day on room exit, 0-23
8. entry time - time of day on recorded room entry in Morning (1), Afternoon (2), Evening (3), and Bedtime (4)
9. exit time - time of day on recorded patient room exit, 1-4
10. entry day of week - day of week on recorded patient room entry, 1-7
11. exit day of week - day of week on room exit, 1-7
12. location X coordinate - x coordinate of patient room on the ICU floor plan
13. location Y coordinate - y coordinate of patient room on the ICU floor plan
14. previous duration (s) - duration of the same staff's previous patient room visit in seconds
15. previous washed on entry - dispenser activation on previous room entry TRUE/FALSE
16. previous washed on exit - dispenser activation on previous room exit TRUE/FALSE
17. previous location - previously visited patient room number

4.2 Feature Selection

After we transformed the dataset into a features set, we executed a feature selection process to automatically select feature subsets in our transformed data that best (1) reduced overfitting of data, (2) improved classification accuracy, and (3) decreased model training time (Guyon and Elisseeff, 2003). Although we do not have a significantly large feature list produced for this ICU, it is still useful to apply this technique to select the most relevant subsets of features to help produce the most accurate feedback in the next step.

To automatically select features from the transformed dataset, HyPo applies a supervised attribute selection filter from the open source Weka Java library (Hall et al., 2009). The filter is composed of two pieces: (1) a feature *Evaluator* to determine how features are evaluated and (2) a *Search Method* to navigate the feature's search space. Our app runs feature selection using the following pairs of *Evaluators* and *Search Methods*, as shown in Table 1:

1. *Evaluator*: CfsSubsetEval that evaluates a subset of features by considering each feature's predictive ability and the degree of redundancy between them.

Search Method: GreedyStepwise with a backward search through the space of attribute subsets.

2. *Evaluator*: InfoGainAttributeEval that evaluates an attribute's worth by measuring the information gain with respect to the class variable to classify.

   Search Method: Ranker that ranks features by their individual evaluations with an optional parameter of 6 features in the output subset

3. *Evaluator*: WrapperSubsetEval (Kohavi and John, 1997) with NaiveBayes (John and Langley, 1995) as the basic learning scheme and a 10-fold cross validation to use for estimating accuracy.

   Search Method: GeneticSearch that performs a search using the simple genetic algorithm (Goldberg, 1989)

Evaluator	Search Method
CfsSubsetEval	GreedyStepwise
InfoGainAttributeEval	Ranker
WrapperSubsetEval	GeneticSearch

Table 1: Evaluator and Search Method Pairs Used in Feature Selection

Our previous study (Zhang et al., 2016) observed two highly correlating factors of compliance using the data collected in the same 30-bed ICU. We could configure HyPo to select only these two features from the dataset to use for determining feedback provision. However, automatic feature selection is an integral piece because as the dataset increases in size and dimension, our enhanced app can continuously combine features or intelligently adjust the correlating features to maximize classification accuracy.

5 FEEDBACK SERVICE

This section first describes the machine learning models employed by HyPo and then presents the feedback service that uses these models to provide timely feedback and to complement the direct observation approach to hand hygiene compliance monitoring.

5.1 Machine Learning Models

After preparing the dataset, we split the data to 65% for training, 10% for cross validation, and the remaining 25% for testing the ML models. Based on the compliance prediction observations from the previous study in (Zhang et al., 2016), we employed the top three classifiers, one from Weka (Hall et al., 2009) and two deep nets from DeepLearning4J (DL4J) (Team,) to serve as our models for classifying *washed on entry* and *washed on exit*. HyPo then uses the results with highest accuracy.

- The **Sequential Minimal Optimization** (SMO) implementation of the Support Vector Machine (SVM), which uses heuristics to partition the training problem into smaller sub-problems and uses pairwise linear regression to classify. This method is usually resilient to data overfitting and by default normalizes the input data (Platt et al., 1998).
- The **Feed-Forward Neural Network** (FFNN), which is a one direction (from input to output) artificial neural network that performs classifications based on weight calculations of the network nodes (Glorot and Bengio, 2010). Using the DL4J Java library, we developed a 3-layer FFNN with a random seed of 6, 1000 iterations, a learning rate of 0.1, and the Stochastic gradient descent optimization algorithm (Gardner, 1984).
- The **Recurrent Neural Network** (RNN), which has a feedback loop whereby the immediately previous step's output is fed back to the net to affect the outcome of the current step. We used a 3-layer RNN with two Graves' Long Short-Term Memory (LSTM) layers (Graves, 2012) (input and hidden) and an output layer along with the same parameters as the FFNN.

5.2 Just-in-Time Alerting

With our previously characterized predictability of compliance (Zhang et al., 2016), as described in Section 2, and necessary pre-configurations to the data collection instruments, HyPo can provide just-in-time alerting to remind HCWs to perform hand hygiene when they are predicted not to comply, using either a *singular* prediction or a *chain-prediction* scheme, depending on if there is adequate time to provide such notifications between each hand hygiene opportunity.

Suppose that HyPo has just observed a staff nurse's compliance on a patient room entry, then the ML classifiers will predict the same staff's exit compliance. For instance, if the staff is predicted to be non-compliant, an alert of red flashing light can be sent to either the wearable badge or the device at the appropriate dispenser activation station as a reminder to the staff; otherwise, no alert is necessary.

If duration of the visit is too short of an interval to send the notification signal to the devices, then we can use the probability chain rule(Schum, 1994) to provide a backup alert to the same staff if necessary. In this case, the ML models will use the predicted entry compliance for the current visit (from the staff's exit compliance of the previous visit) to determine exit compliance of the current visit at a probability of 89% * 77% = 69%. It is less ideal, but the likelihood of the visit interval being too short is minimal because the grace period for compliance is set at two minutes, and if a room visit is within two minutes, hand hygiene compliance is not required.

5.3 Recommend Training Material

If a staff member is frequently predicted as non-compliant over a long observation period, HyPo (with integrated email capabilities) can recommend hand hygiene guidelines or appropriate training materials to the staff via email. The goal is to improve compliance on an individual basis.

5.4 Assist Direct Observation

The compliance prediction results can also be used to assist the current standard practice of direct observation. With predicted non-compliance reoccurring at a certain location (*i.e.*, a patient room), HyPo can deploy a human auditor (*e.g.*, by sending a notification) to observe compliance at the location that should be given most attention.

6 RELATED WORK

Due to worldwide high demands of HAI prevention, a number of other researchers have studied approaches to improve hand hygiene compliance. Although the gold standard monitoring method is human-centric (WHO, 2009), (Gould et al., 2011), a wide rage of studies propose electronic or electronically assisted hand hygiene compliance monitoring and intervention systems (Ellingson et al., 2014), (Ward et al., 2014). This section compares our work on the HyPo app with common electronic intervention systems including (1) technology-assisted direct human observation, (2) counting systems, and (3) automated monitoring systems.

Technology-Assisted Human Observation Direct observation is the most precise way of controlling compliance. Several studies use technologies such as handheld devices and cameras to aid human observation, aiming at reducing input errors, costs, and time consumption. Handheld devices are used for data entry, and video cameras provide opportunities to reduce the Hawthorne effect and observe locations that are remote or hard to access.

Chen et al (Chen et al., 2013), used wireless data entry devices and a website to allow human observers to audit compliance. University of North Carolina Hospitals implemented a “clean-in, clean-out” system that allowed covert observers and designated nurses to track compliance using a mobile app and a web portal (Sickbert-Bennett et al., 2016).

Cameras have been used by Armellino (Armellino et al., 2013) to increase compliance in an ICU. The study connected motion sensors near the sinks that would activate cameras being monitored by remote auditors. The study by Davis (Davis, 2010) placed a discreet camera at the entrance of a ward and assessed compliance before and after a sink was placed pointing to the dispenser.

Unfortunately, these methods still require human interaction and can bias the results, as the medical workers know they are being directly observed. Moreover, audits require trained personnel who are regularly monitored to ensure quality control.

Counting Systems Installing counting devices to measure the remaining sanitation product volume or the number of dispenser activation times is a quiet method that is not subject to the Hawthorne effect. A counter may detect usage patterns and frequency changes.

Marras (Marra et al., 2010) used dispenser counters along with direct observation to assess whether positive deviance in hand hygiene behaviors could have an impact on reducing HAIs. A downside to this approach, however, is that counter systems cannot tell who used the dispensers and therefore are unable to evaluate compliance by itself. Morgan et al (Morgan et al., 2012) provide evidence to support the claim that dispenser usage data could be more reliable than direct human observation to estimate hand hygiene compliance.

Automated monitoring systems using wearables Many automated monitoring systems are capable of producing feedback or reminders in real or near real time without human intervention, similar to our approach.

Fakhry used a motion-triggered system with audible hand washing reminders at each medical department entrance (Fakhry et al., 2012). Sahud and Bhanot developed an electronic hand hygiene feedback device that reports real-time compliance rate on a liquid-crystal display visible to all staff in the intervention unit (Sahud and Bhanot, 2009). Edmond et al installed a sensor network using a credit-card sized sensor badge on each alcohol dispenser, which when not activated on room entry or exit beeped with a red indicating light (Edmond et al., 2010). Similarly, Marra et al employed a wireless network with sensors on the alcohol dispensers that provide real-time flashing light feedback to HCWs for hygiene activity detection (Marra et al., 2014). Most recently, Ellison et al proposed a prospective electronic hand hygiene room entry/exit audible reminder system (Ellison et al., 2015) that provides a combination of 24-hour-a-day recording of hand hygiene activities and real-time computer monitor performance feedback.

Differentiating Factors of Our Approach All the prior research we reviewed collected data to propose strategies that increased hand hygiene performance or gather conclusions regarding the efficacy of a specific approach. Our HyPo app is unique since it uses the gathered data to predict future compliance behavior instead of notifying appropriate caregivers after non-compliance has been detected. Other approaches *react* to non-compliance, while ours *predicts* compliance ahead of time.

We presented a novel methodology using ML algorithms, which is also unique to our work. Hence, the aim of our work is also a differentiating factor. In particular, HyPo evaluates the prediction capabilities of different ML algorithms to predict compliance ahead of time.

7 CONCLUDING REMARKS

This paper presented a hand hygiene monitoring app called Hygiene Police (HyPo) that can be deployed as a service to complement the current monitoring approach and improve compliance. We showed an example data collection process taken place at a 30-bed ICU where we acquired the handwashing compliance data. We also described the data transformation process HyPo employs to maximize the utilization of the selected machine learning (ML) classifiers.

Combining the results of real-time compliance predictions using the correlations identified in (Zhang et al., 2016), HyPo can provide three types of services: (1) just-in-time alerting to remind predicted non-compliant staff to perform hand hygiene, (2) recommending training materials to habitually non-compliant staff via email, and (3) assisting the direct observation approach by deploying human auditors at the opportune time and place when and where non-compliance is frequently predicted to occur. We also compared our app to related research work and found that our approach *p*redicted future compliance behavior instead of *r*eacted to non-compliance as in other approaches. Our methodology using ML algorithms is unique and is the only work that evaluates ML prediction capabilities in this domain.

In future work, we plan on collecting more compliance data, ideally using the same process as discussed in the paper. We will use this data to fine tune the parameters in our ML classifiers to increase the prediction accuracy. We will also run simulations that test whether our HyPo app can improve compliance in general and if the improvement can be sustained over time in a range of caregiving settings.

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