Automatic Hand Hygiene Monitoring Systems for Infection Prevention in Healthcare Settings: A Short Review of Literature

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Abstract— **Healthcare-associated infections (HAIs) remain a global challenge, with significant morbidity, mortality, and economic implications. Improving Hand Hygiene (HH) compliance is one of the most effective strategies for reducing HAIs. However, compliance rates remain suboptimal. Electronic Hand Hygiene Monitoring Systems (EHHMS) have emerged as a promising solution to address this challenge by providing real-time feedback and promoting behavior change among healthcare workers. This narrative review examines the methodologies used in EHHMS, classifying them into four key categories: rule-based systems, signal processing, machine learning, and data fusion approaches. Rule-based systems, though widely used, are limited by their static nature and inability to adapt to dynamic healthcare environments. Signal processing methods focus on localizing hand hygiene events, while machine learning (ML) approaches mostly focused on HH quality. Data fusion techniques improve monitoring by integrating inputs from multiple sensors. Despite their potential, EHHMS face challenges in accuracy, intrusiveness, and integration into clinical workflows. This review highlights the potential role of ML in overcoming these limitations. By addressing current barriers, EHHMS can play a crucial role in enhancing HH practices and reducing HAI rates, ultimately improving patient safety and healthcare quality.**

Keywords— **Electronic monitoring, Hand hygiene compliance, Healthcare-associated infections, Infection prevention and control**

INTRODUCTION

Healthcare-associated infections (HAIs) represent a major global health challenge and are one of the important causes of morbidity, mortality, and economic costs [1]. HAIs pose a significant threat to the healthcare system. In high-income countries, 7 out of 100 hospitalized patients contract an HAI, whereas in low- to middle-income countries, the rate is higher at 15 out of 100 patients [2]. The prevalence of HAIs is 0.14% on a global scale and the impact continues to grow by 0.06% annually [3].

Unfortunately, the research suggests that the pattern of HAI rate is not following a declining trend [4]. According to the World Health Organization (WHO), effective infection prevention and control programs can reduce HAIs by up to 70% [2]. Therefore, there is a need for effective strategies in HAI prevention and control.

One of the most important strategies to prevent the spread of HAI is increasing adherence to Hand Hygiene (HH) protocols [5]. HH includes handwashing with soap and water or the use of alcohol-based hand rubs (ABHRs). A 2021 systematic review including 35 different studies suggests that the HH compliance rate is somewhere between 60% to 70% [6]. Factors such as forgetfulness, lack of knowledge, high workloads, inadequate staffing, and poor access to HH supplies contribute to these low compliance rates [7].

To address HH challenges, Electronic Hand Hygiene Monitoring Systems (EHHMS) have been introduced. These systems aim to provide real-time feedback on HH compliance, thereby promoting behavior change among healthcare workers (HCWs) [8]. This paper aims to review the foundational algorithms and methodologies that EHHMS recruit to improve HH compliance and reduce HAIs.

METHODOLOGY

A thorough search was conducted across databases including PubMed, Scopus, IEEE Xplore, Web of Science, Google Scholar, and the University of Toronto Library using keywords such as “Hand hygiene monitoring systems,” “Automated infection prevention,” “Hand hygiene compliance” AND (“electronic monitoring” OR “automated systems”), and “Hand hygiene monitoring” AND “infection control.”

For our literature review, we used Covidence software to manage and screen relevant articles. We manually downloaded bibliographic data from PubMed, Scopus, IEEE Xplore, and Web of Science. Due to Google Scholar's lack of an efficient bulk export feature, we developed a script to automate citation retrieval. The script, available at *https://github.com/shaychavoshian/Automated-Citation-Retrieval*, interfaced with Google Scholar to collect bibliographic details such as titles, authors’ names, publications’ year, journal names, and abstracts. These citations were exported into RIS format for reference management, with batches saved and a delay included between requests to avoid overwhelming the server and triggering anti-bot measures.

Studies were included if they evaluated the effectiveness of EHHMS in healthcare, assessed their impact on HH compliance or HAI rates, and were peer-reviewed in English. Exclusion criteria included literature reviews, conference abstracts, and publications before 2015. Titles and abstracts were screened, and full-text reviews confirmed eligibility. Data extracted from the final selection included study design, methodology, technology used, and outcomes on hand hygiene compliance and infection rates.

RESULTS

A total of 2,501 studies were found out of which 1,091 were duplicates. Out of the 1,410 articles, 453 were selected for the full text review. Eventually, using the mentioned inclusion criteria 10 studies were selected to be reviewed in this short review paper. These 10 studies were carefully selected to represent the general trends in approaches and methodologies within the field.

Electronic HH monitoring systems use various sensor technologies, including radiofrequency identification (RFID), infrared (IR) sensors, and video monitoring. The methodologies can be categorized into several key algorithmic approaches as follows:

Signal Processing Algorithms: Hadian et al. developed and evaluated a room-level localization system using Bluetooth Low Energy (BLE) technology to enhance HH compliance [9]. The system aimed to enhance HH compliance estimation by localizing HCWs in patient rooms using four BLE beacons. Nine participants were recruited to test beacon placements to identify four zones in a patient room: entrance, sink area, the left and right sides of the bed. The highest F1-score achieved was 0.67 using all four beacons. Challenges included signal noise, non-line-of-sight issues, time-consuming room-specific fingerprinting, low data collection rate (1 Hz), and potential RF interference with medical devices.

Li and his colleagues developed WristWash, a device for assessing handwashing quality [10]. The wrist-worn device with an IMU, tracked hand movements and was tested in a lab with 12 participants. It achieved 92% accuracy in user-dependent models and 85% in user-independent models. A key limitation of their system was that wristband pose an infection risk and might not be permitted in every healthcare setting.

Machine Learning Algorithms: Machine learning (ML) algorithms have the potential of playing a crucial role in improving the accuracy of HH compliance detection particularly by measuring the quality of handwashing. For example, Camilus and Lee proposed an automated hand washing monitoring system using depth sensors and ML techniques [11]. The system used Near-Field Magnetic Induction for user identification and depth cameras to monitor hand washing. A deep learning model was proposed to identify WHO-recommended hand washing poses with an accuracy of 96.8%.

In another study by Zhong et al., a depth sensor was mounted above a wash basin to monitor hand washing steps[12]. The system recorded depth maps of hand movements during handwashing. It featured a decision tree classifier for ensuring hand washing gestures adhered to WHO guidelines, without requiring hand instrumentation. Tested with 15 participants, it achieved up to 94% accuracy in gesture detection.

Banerjee et al. developed a system to improve hand washing compliance using Myo armbands with IMU sensors [13]. The system applies Dynamic Time Warping (DTW) and Support Vector Machine (SVM) for recognizing HH steps per WHO/CDC guidelines. They collected data from 20 participants and achieved an accuracy of 88%, precision of 0.89, and recall of 0.85 using a 10-fold cross validation. This method could identify missing components in around 350 out of 500 non-compliant hand wash routines. These systems evaluate the action of hand washing but not whether HH is done at the right time.

Rule-Based Algorithms: Rule-based algorithms operate on predefined logical conditions and are widely used in EHHMS for event detection. These systems rely on if-then rules to assess compliance, such as triggering an alert if HH is not performed within a specified time after patient contact. Rule-based systems are simple but can be limited in handling complex scenarios compared to ML-based methods.

A study in the UK evaluated the impact of EHHMS on HH compliance and behavior in healthcare settings [14]. The system included badges with alcohol sensors in conjunction with ceiling sensors to identify different zones. These sensors triggered visual and auditory signals to provide real-time reminders to HCWs. Involving 12 HCWs, the study demonstrated a significant increase in HH compliance from 73% to 83% during the implementation of the EHHMS. Following system removal, compliance reverted to the baseline level of 73%. Concurrently, alcohol-based hand sanitizer consumption increased from 4 liters to 10 liters during the intervention period. Fernie et al. presented a multiphase testing of an automated reminder and monitoring system in a complex continuing care setting [15]. Their technology included chest-worn badges, zone markers to track room entrances and exits, and dispenser counters to monitor alcohol-based hand sani-

tizer usage. The study included five phases: baseline, pre-intervention with status indicators, two intervention phases with reminders and feedback, and post-intervention with status indicators only. Despite the increase in HH performance, its setting in a continuing care unit limited generalizability to other clinical environments. The study highlighted the progression of automated HH monitoring technology, its potential to enhance healthcare practices, and the challenges of implementation.
The study of Marra et al. aimed to evaluate the effectiveness of a real-time feedback system in enhancing HH compliance in a medical-surgical step-down unit [16]. The system used electronic handwash counters with wireless Zigbee technology and identification badges for HCWs. It provided immediate feedback by flashing a red light if HH was not performed and a green light if it was. HH compliance improved significantly, with HH episodes increasing from 74.5 to 90.1 per patient-day (P = .01) and alcohol-based handrub use rising from 68.9 to 103.1 mL per patient-day (P = .04). Challenges included calibrating badge detection distance to avoid interference from adjacent beds and ensuring signal accuracy despite physical barriers.

Data Fusion and Aggregation Algorithms: Data fusion and aggregation algorithms combine data from different types of sensors to provide a comprehensive analysis of HH compliance.

Fisher and his colleagues' objectives were to validate a novel method for assessing HH compliance using ultrasound transmitters in patient zones and receivers tagged to staff [17]. The secondary objective was to assess the impact of audio reminders and quantified individual feedback on HH compliance. The study used a Wireless EHHMS with protection zone transmitters, wash transmitters, wireless tags, and reader units. Zones were created around patient beds, and ABHR dispensers were equipped with transmitters to monitor HH events. Laboratory tests, a simulated exercise, and comparisons with manual observations validated the system. The system underestimated HH opportunities by 10.2% and compliance by 5.2% compared to manual observation but was found valid for auditing HH compliance. Results showed that electronic monitoring provided a modest short-term improvement in HH compliance.

In an exploration, SinkNet, a system integrated into a regular sink, was developed and evaluated [18]. SinkNet transformed a conventional sink into a smart device using sensors to monitor water usage, handwashing habits, and other activities. It included flow and temperature sensors and transmitted data to a private network for analysis. Installed in a controlled environment, the system was tested with simulated sink activities. Results demonstrated that SinkNet effectively monitored and analyzed sink usage patterns.

DISCUSSION

Most current studies on HH monitoring have primarily relied on rule-based systems. Figure 1 shows the proportion of different algorithms we came across in our literature review.

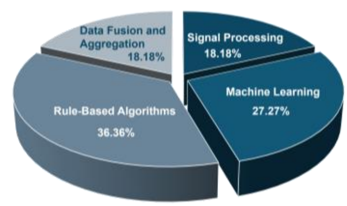

Figure 1: The proportion of different EHHMS algorithms.

The rule-based systems are designed around fixed algorithms and thresholds that use predefined guidelines to determine compliance. For example, sensors might detect when a HCW enters or exits a patient's room, and compare this data to a set of established HH protocols [19]. While some of these rule-based systems have had notable success in healthcare settings, they come with limitations that hinder their full potential in promoting HH compliance [20].

A major limitation of rule-based systems is their inability to adapt to new or unexpected situations. These systems are static in nature and do not adapt well to the complexity and variability of healthcare environments. The rigid framework of rule-based systems can therefore miss subtle compliance issues, leading to inaccurate assessments of HH practices. There is, however, a significant opportunity for ML to address these limitations and enhance the effectiveness of HH monitoring [21].

Unlike rule-based systems, ML models have the potential to learn from large, diverse datasets, enabling them to offer more personalized and context-aware assessments of HH behavior. ML models can dynamically adapt over time, improving their predictive capabilities as they are exposed to more data.

The majority of existing ML applications in HH monitoring focus primarily on assessing handwashing quality and correctness. There is significant opportunity for ML to expand its role by detecting various HH actions including the use of ABHR, identifying HH moments, and calculating compliance more accurately. Additionally, ML could be leveraged to analyze contextual factors, predict high-risk non-compliance scenarios, and provide personalized feedback to HCWs.

Further research is needed to explore the practical implementation of ML in HH monitoring, and to better understand how it can be integrated with existing healthcare systems to maximize its impact.

CONCLUSION

EHHMS have demonstrated promising outcomes in promoting HH practices. Further research and development are needed to address the gaps identified. While rule-based systems have laid the groundwork for HH monitoring, the future of infection prevention in healthcare settings lies in the integration of ML. The ability of ML to offer personalized, context-aware insights, adapt to evolving data, and provide real-time feedback could significantly enhance HH practices and, in turn, reduce HAIs.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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