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Infection Control in Digital Era: Future or Futile?

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ABSTRACT

New technologies are being developed and marketed to healthcare facilities all over the world as a way to stop healthcare- associated infections. The Internet of Things and artificial intelligence have been created with a variety of capabilities to improve people's health, offer necessary services, and monitor their health The potential adoption of these technology in automated surveillance and automated hand hygiene compliance monitoring systems has a lot to offer health care systems. However, the success or failure of the use of technology will depend on the awareness of the challenge and the establishment of a strategy, goals, and processes to support technology deployment, maintenance, and training. System differences between nations and a lack of standardization in the application of digitalization in health care hinder this technology from providing the full range of potential benefits. In this review, we explore the use of technology in the areas of automated infection surveillance in healthcare-associated infection and hand hygiene compliance, with an emphasis on the difficulties in developing such technologies.

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Introduction

Digital technologies are becoming increasingly important in almost every aspect of life. A wide range of digital health technology (DHT), including Internet of things (IOT) and artificial intelligence (AI), Mobile health applications, telehealth services and big data are widely employed in health care service, and a slew of solutions have arisen to mitigate the impact of COVID-19 (Vaishya et al., 2020; Vidal et al., 2020). The COVID-19 has greatly accelerated digitalization and introduced new challenges and potential for infection prevention and control (IPC) (Javaid et al., 2020; Kalhori, et al., 2021). It has prompted healthcare systems to use new IPC technology and approaches (Vidal et al., 2020; Wang et al., 2020). which can improve the system's usability, efficacy, and level of care (Fitzpatrick et al., 2020; Torous et al., 2020).

Growing healthcare- associated infections (HAIs) reporting rates make it clearer that patient safety, healthcare quality, and preparedness for infectious disease casualties all need to be improved. As a result, surveillance measures act as the first line of defense against HAIs, highlighting the need of implementing efficient surveillance (Degeling et al., 2019; Parreco et al., 2018; Villamarín et al., 2020). The Traditional HAIs surveillance approaches are considered a sort of passive monitoring, which depends on case reporting through manual screenings however, it has shown to be time-consuming and unreliable (Du et al., 2014; Streefkerk et al., 2019). Meanwhile, with modern health care technology, monitoring can be aided by the use of the sophisticated algorithms machine learning (ML) and deep learning (DL) that built on data seek to early detection populations at-risk and keep track of an estimate of the prevalence of HAI to improve the emphasis of preventative interventions (Parreco et al., 2018; Li et al., 2019; Liao et al., 2019). By adopting automated monitoring and infectious disease detection methods, hospitals can improve the quality and safety of patient care (Streefkerk et al., 2020; Yesmin et al., 2022).

Handwashing is an easily accessible and cost-effective infection control behavior to reduce HAIs. The COVID-19 pandemic has renewed calls for increased handwashing to stop the virus's spread (Stangerup et al., 2021). Despite this the compliance is very low (Stangerup et al., 2021). Hand hygiene compliance (HHC) continues to be a global challenge, indicating that knowledge and awareness are insufficient to change behavior (Sadule-Rios& Aguilera, 2017; Clancy et al., 2021). A crucial component of multimodal techniques to enhance hand hygiene (HH) is monitoring HH. Direct observation (DO) is the gold monitoring standard for calculating HHC rates (Gould et al., 2017). However, the process is still not standardized, Hawthorne effect, which outlines how providers' behaviour changes when they realize that they are being monitored has sparked interest in new methods for checking HHC and prompted the creation of automated HH monitoring systems (AHHMSs) (Gould et al., 2017; Kelly et al., 2021; Wu et al., 2018). It can track hand hygiene compliance in "real time," avoiding the Hawthorne effect and allowing for more efficient data collecting for large groups of people (Kelly et al., 2021).

In this review, we examine the potential advantages of IPC digitalization for automated infection surveillance, predication of healthcare-associated infections and hand hygiene compliance. highlighting the challenges associated in implementing such technology.

Applications of Digital Technology in infection control

Automated Surveillance

Surveillance is crucial for infection control because it determines which prevention strategies should be given priority and enables programs to assess the success of their prevention efforts (Degeling et al., 2019; Cha & Kim, 2020). Technological developments and the gradual digitalization of health data enable more hospitals use electronic medical records (EMR) for automated HAIs surveillance. it is an innovative way to lower the infection incidence and produce novel disease control because it has been demonstrated to be more effective, reliable, lower costing and safe time in detecting infections than traditional surveillance (Streefkerk et al., 2019; Kelly et al., 2021). The efficiency of automated surveillance was revealed in many studies for instance, Real time nosocomial infection surveillance system (RT-NISS) was developed and validated in China by Du et al in 2014. The sensitivity and specificity of automatic hospital-wide HAIs surveillance system RT-NISS were 98.8% and 93.0% respectively, when compared to a manual survey of nosocomial infections (Nis) (Du et al.,2014). Study done by Blacky et al, in Vienna General Hospital showed that automated MONI-ICU (monitoring of nosocomial infections in intensive care unit (ICU) gives surveillance staff and physicians almost-real-time view of clinical markers for NIs with sensitivity, 90.3% (Blacky et al., 2011). Moreover, the InNoCBR system, which was developed between 2010 and 2013, is an automatic HAI detection and categorization software that is commonly utilized at CHUO's Preventive Medicine (Ourense University Hospital Complex, Spain). Since its implementation at more hospitals in Galicia (Spain) in 2013, the InNoCBR system has become the standard system for HAI surveillance. InNoCBR achieves a high level of sensitivity (81.73 percent), specificity (99.47 percent), and a good positive predictive value (94.33 percent) when tested against the gold standard (Villamarín et al., 2019).

The potential impact of using AI tools in numerous aspects of healthcare is becoming more generally recognized. AI systems will be able to analyses, diagnose, and provide decision support for prevention and early intervention (Fitzpatrick et al., 2020; Li et al., 2019). ML, a subset of AI technology, can be used in clinical microbiology labs to identify and forecast diseases, enhancing patient safety. DL, a recently developed area of AI, has boosted accuracy greatly by utilizing new strategies, specialized software, and vastly larger datasets to find more complicated correlation in the data (Tobore et al., 2019). Park et al. published a study in 2021 that attempted to develop prediction models that physicians might utilize in the hospital setting to make clinical decisions based on DL and ML using laboratory data. The study found that using DL and ML might produce more accurate diagnosis findings than physicians (Park et al., 2021). AI usage for prediction or early detection of HAIs has a lot of potential in IPC (Fitzpatrick et al., 2020). For instance, the risk of nosocomial *Clostridium difficile infection* (CDI) has been predicted using ML technologies (Oh et al., 2018; Li et al., 2019). Parreco et al. investigated the effectiveness of three different ML-based models for the prediction of Central Line-Associated Blood Stream Infection (CLABSI). this study revealed that models for predicting patients with CLABSI had the highest accuracy, precision, sensitivity, and negative predictive value (Parreco et al., 2018). The quality, cost, and outcome are all impacted by the necessity of early diagnosis of these individuals (Parreco et al., 2018). The study established a non-invasive examination and inspection approach for ventilator-associated pneumonia (VAP) diagnosis using an electronic nose. The results show that an ML-based electronic nose can help patients gradually attain the idea of high-quality medical care while also improving their quality of life. 2019 (Liao et al.). The application of AI can improve patient risk assessment, provide real-time detection for more focused surveillance, and enable the development of targeted IPC interventions.

Automated hand hygiene compliance

HHC is one of the most important factors in reducing HAIs, and accurate HHC monitoring among health professionals is essential to delivering high-quality care. The gold standard method for evaluating HHC is DO and feedback, as measured by hospital auditors (Gould et al., 2017). However, the observation bias and the requirement for numerous observers over a long period of time limit its effectiveness. (Gould et al., 2017; Wu et al., 2018). With the help of automated HH-measuring technologies, IOT has a lot of potential to improve HHC. Xu and colleagues in 2021 investigate the impact of an IoT-based management system on HHC in a critical care unit. They found that although there was no decrease in NIs, the new method increased the rate of HHC among all workers (Xu et al., 2021). In another study in a hospital setting in Ontario, Canada to investigate the impact of IoT interventions on patient safety measures such as patient falls and HHC. It emphasized several key points about the use of IoT in healthcare. The HHC rates were increase in the first year followed by a reduction in the second year (Yesmin et al., 2022). Similarly, a study done by Marques et al, 2017 using IOT based automated monitoring systems in conjunction with gamification to enhance HHC among HCWs showed that there was an improving in the awareness of nurse HHC (Marques et al., 2017).

AI applications in hospitals have a significant impact on HHC. Computer vision, a type of AI, could provide a novel approach for performing more accurate and privacy-protected hand hygiene assessments. Depth pictures, which simply capture an image without allowing identification of the persons being watched or the ability to identify characteristics, are used to allay concerns about the use of video surveillance in places where privacy is a concern (Awwad et al., 2019). In the study by Awwad et al., it was discovered that the system was more successful at identifying the supply of alcohol hand rub when it used computer vision and depth images for hand hygiene auditing. The study demonstrated that it could automate the direct observation of hand hygiene practice, which boosts clinical application and decreases privacy concerns (Awwad et al., 2019). The simplicity and accessibility of the dispenser allows for a stronger habit of hand washing, which has substantial potential benefits. Singh discovered that using a computer vision system to track use of hand sanitizer dispensers was equivalent to human observation. Given its capacity to be passive, inexpensive, privacy-safe, and sensitive, it may be helpful in attempting to eliminate an apparent recurring source of healthcare-induced harm due to its capacity to provide ongoing monitoring and feedback to clinicians (Singh & Sittig., 2020). On the other hand, hand sanitizer uses, or automatic dispenser activation counts cannot be used to assess HHC. As a result, the importance of embedding real-time feedback into AI applications to promote behaviour change has increasingly been emphasized (Lacey et al., 2020). Lacey and coworkers deployed an autonomous video auditing (AVA) system with real-time feedback at handwashing. The findings revealed that using AVA in conjunction with electronic monitoring enables for simultaneous auditing of providers' handwashing quality and quantity. But when the feedback was taken away, performance went back to normal (Lacey et al., 2020). Furthermore, according to a study done to evaluate the influence of The Sanibit electronic HH system on HHC and quality changes over time in ICU, a sensor-based platform with automated HHC and real-time feedback increased providers' HHC in an ICU (Xu et al., 2021).

Recently, the potential health benefits of wearable hand hygiene technology have received a lot of attention in the medical community. Some study has been done in hospital hand hygiene monitoring using wearable sensors (Li et al., 2019). Wearables-based systems does not require the installation of a camera, and it typically captures wrist movement data during a handwashing event using sensors, to detect handwashing steps in compliance with WHO recommendations. Wrist Wash (Li et al., 2019) is a widespread procedure involving the use of a wrist-worn platform that allows offline analysis for assessing the stages using a Hidden Markov Model-based method according to WHO criteria (Li et al., 2019). The results showed that user-dependent models had an average accuracy of 92 percent, whereas user-independent models had an average accuracy of 85 percent. However, when that assumption is relaxed, the results for relaxed performance drop considerably, from 85 percent to 69 percent (Li et al., 2019). The accuracy of a sensor wristband in monitoring adherence to WHO hand rub and handwashing guidelines was also tested by Wang et al (Wang et al., 2020). The limitations of camera-based technology were all overcome by this study. However, these are unsatisfactory in terms of gaining accuracy, reminding individuals to wash their hands, and offering feedback on the effectiveness of their handwashing (Wang et al., 2020). Over the years, a number of hand hygiene assessment systems have been developed to evaluate the quality of handwashing. The study on how a wearable device affected HHC and the quality of hand rubbing revealed that while HHC did not improve, the quality of HH activity did, with a substantial increase in both the amount of alcohol-based hand rub (ABHR) utilised and the amount of time spent rubbing hands. (Pires et al., 2021). Smartwatch-based automated systems for higher accuracy assessment handwashing quality have been developed. IWash is a smartwatch-based system for evaluating the effectiveness of handwashing that precisely identifies whether the user followed WHO guidelines or not. It uses voice to remind users to wash their hands frequently, especially as they enter the house, and to provide real-time feedback on the effectiveness of their handwashing (Samyoun et al., 2021).

Challenges

Data accessibility and the availability of sufficiently large data sets with high-quality and reliable data for data analytics are the initial barriers to the effective implementation of DT (Gianfrancesco et al., 2021). Healthcare professionals have spoken about difficulties with the healthcare system's data quality, including a high workload, enormous amounts of unstructured data, a lack of diagnostic code sensitivity, and data extraction, that have an impact on the quality of the data and lead to an inaccurate assessment of the patient's current condition (Ni et al., 2019). Non-standard reporting, a lack of clarity, and a lack of validation are further implementation obstacles (Beam, Manrai, & Ghassemi, 2020). ML outcomes may become less capable of classifying or identifying comparable patterns in new data, depending on how the data was gathered and the learning algorithms were created (Conway., 2016; Park et al., 2021). Liu et al in 2019, provided a users' guide to improving research methodologies and training healthcare professionals particularly clinicians, on the fundamentals of ML, the necessity of efficient ML model validation, and effective methods for integrating ML models into clinical practice. this will make studies more credible and understandable, which will increase user confidence (Liu et al., 2019). Software developers, hospital IT employees, epidemiology experts, and IPC specialists must work closely together for the development and validation phases of data. This guarantees clinical applicability and permits the interpretation of results (Sittig et al., 2020).

The benefits of using technology must be evaluated against the serious ethical and legal concerns. Large-scale patient medical record use and sharing raises concerns about confidentiality and privacy by increasing the possibility of unlawful use, accessibility, and potential abuse of personal data (Kalkman et al., 2019; Char et al., 2020). Furthermore, even when patients have been given assurances of secrecy and privacy, there is a higher possibility that their personal information will appearing on social media when databases are breached (Gilbert et al., 2019). Digital tracking with the intention of conducting public health surveillance, have been found to be closely linked to serious privacy concerns (Zhao et al., 2021). It has been recognized as posing a significant risk to further disclosures of sensitive information. The ethical responsibility of the patient must be respected when using technology in healthcare to bolster the value of privacy (Zhao et al., 2021).

Online resources for infection prevention recommendations are abundant and easy to access. Internet connectivity issues negatively impact data availability and quality (Pollett et al., 2017). Lack of Internet connectivity, along with low Internet quality and stability, greatly hinder the use of digital technologies for infection control.

In Low- and Middle-Income countries (LMICs) with underfunded health systems and fewer providers, it might be crucial to concentrate on digitalization deployment (Jones et al., 2021). Hospitals frequently struggle with staffing and financial issues related to IPC programs. Lack of IPC training for staff members and inadequate adherence to IPC principles could exacerbate these problems (Lowe et al., 2021; Jones et al., 2022). Evaluating the potential and difficulties of implementing technology advancements is crucial to enhance assessments, development, ethics, usage, and monitoring technology techniques that might reduce the local burden in LMICs (Kruse et al., 2019; Jones et al., 2022).

Discussion

The potential use of digital technology in IPC could significantly reduce the risk of the spread of infectious diseases. However, it is limited by the awareness of the IPC challenge, objectives and processes that relate to the health system (Singh & sittig, 2015; Lowe et al., 2021). The effective use of technology to boost safety and infection control is essential for improving healthcare. Therefore, when providing care for their patients, all healthcare professionals must use technology correctly and completely. Inaccurate or inadequate data causes faulty predictions and improper outcomes. Reliability depends on the surveillance system's accessibility and connectivity to the completeness, and validity of EMR data (Streefkerk et al 2020; Gianfrancesco et al., 2021) in-addition to consideration of the ethical issues posed by applying ML in healthcare is necessary (Char et al., 2020). A systems-level approach is required for the optimum suited digital system's strategy, one that connects infection detection with case isolation, follow-up, and monitoring while also selecting the best interventions to control the infection (Beam, Manrai, & Ghassemi, 2020). Automated surveillance systems require monitoring systems to find problems and their causes, as well as ongoing maintenance and quality control, to assure improvements. Both the software and the methods need to be evaluated and perhaps updated in order to deliver safe and effective care (Siting et al., 2020).

The development of AHHMSs provided reduction in observation bias and offer the chance to continuously monitor and enhance hand hygiene procedures (Pires et al., 2021; Lacey et al., 2020). The ability of any technology to be successfully embedded into the healthcare system is crucial. However, concerns over privacy are known to have an impact on HCWs' attitudes regarding automated monitoring (Awwad et al., 2019; Wang et al., 2020). They believe that these systems violate their right to privacy leads to refuse to change HH practices (Conway et al., 2016). The limitations of the algorithm must be considered before implementing AHHMS. The ML algorithms used to determine compliance with hand hygiene recommendations may produce inaccurate classifications that impair system accuracy (Wang et al., 2020). Moreover, the deployment of AHHMS at a healthcare facility is expensive requires infrastructure upgrades and maintenance expenses (Conway et al., 2016). The hospital system must be improved before addressing HHC to reduce HAIs. To accomplish this, future automated HH challenges should be addressed through additional research on the impact of systems on HH practices, the implementation of novel training and educational initiatives, and the determination of the best monitoring methods for improving monitoring outcomes.

Conclusion

Although the advent of digitalization in infection control holds out the prospect of real improvements in global public health, there are still many obstacles in the way, including issues with people's awareness of digital infection surveillance systems, their knowledge of HHC, and their concern for their privacy on maintaining data integrity and security. The healthcare system must weigh the benefits and drawbacks of these developing technologies to select the appropriate digital tools for their particular requirements and budgetary constraints additionally, the limitations of their infrastructure and organizational culture. Moreover, research are needed to determine whether using clinicians and healthcare experience in the context of enhancing infection control with digital technology is appropriate.

Conflict of Interest

There are no conflicts of interest.

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