Brief Report

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Effectiveness of an artificial intelligence-based training and monitoring system in prevention of nosocomial infections: A pilot study of hospital-based data

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SUMMARY This work describes a novel artificial intelligence-based training and monitoring system (AITMS) that was used to control and prevent nosocomial infections (NIs) by improving the skills of donning/removing personal protective equipment (PPE). The AITMS has two working modes, namely an AI-based protective equipment surveillance mode and an AI-based training mode, that were used for routine surveillance and training, respectively. Data revealed that the accuracy rate of donning/removing PPE improved as a result of the AITMS. Interestingly, the frequency of NIs decreased with the use of the AITMS. This study suggested the key role of using PPE in controlling and preventing NIs. Data preliminarily proved that appropriate donning/removing PPE may help to reduce the risk of NIs. In addition, the newest computerized technologies, such as AI, have proven to be useful in controlling and preventing NIs. These findings should helpful to formulate a better strategy against NIs in the future.

Keywords artificial intelligence, nosocomial infection, surveillance, training, artificial intelligence-based training and monitoring system (AITMS)

1. Introduction

The term "nosocomial infections (NIs)" is used to describe all infections acquired in a hospital. NIs have several characteristics that differ from community-acquired infections: *i*) NIs are healthcare-associated infections that are acquired after hospitalization and that manifest 48 hours after admission (*1*). Due to their considerable impact on clinical outcomes, some authors have proposed that the period for NIs should be extended to within 30 days of hospital discharge or 90 days after undergoing surgery (*2*). *ii*) NIs can be systemic; common NIs are pneumonia (hospital-acquired or ventilator-associated), urinary tract infections (catheter-associated), surgical site infections, central line-associated bloodstream infections, and *Clostridium difficile* infections (*3*). *iii*) Patients, relatives of the patient, caregivers, and medical personnel may be involved. *iv*) NIs are often associated with medical interventions, such as surgery, medication, or invasive examinations. *v*) NIs readily occur in departments dealing with critical illnesses, such as the transplantation unit, chemotherapy unit, burn unit, or intensive care unit. *vi*) NIs can often be monitored and dealt with. NIs have been the sixth leading cause of death in United States (*2*). As a notable but intervenable cause of death in the hospital, NIs are of great concerned to clinicians and governments around the world. Indeed, NIs are commonly problematic because most NI-related pathogens, be they bacteria (*4*) or fungi (*5*), have natural resistance to empirical antibiotics and thus cannot be treated with commonly used antibiotics. Moreover, most people who contract an NI are older, neonates, those who are immunocompromised, or those who are suffering from chronic diseases. The clinical outcomes and quality of life (QOL) of patients markedly worsen once they develop an NI. Fortunately, however, NIs can be dealt with and prevented since they are hospital-related infections. In line with World Health Organization guidelines, the incidence of NIs can be reduced approximately 70% by satisfactory infection prevention and control programs (*6*). The vast majority of countries have set up surveillance and information sharing systems to fight against NIs (*7*). To the extent known, however, merely creating such systems without specifying their detailed operation in clinical practice might yield limited achievements in terms of reducing the frequency of NIs. Hence, many practical measures are taken to reduce the risk of NIs in routine clinical tasks, such as using personal protective equipment (PPE). PPE is used to reduce the exposure risk of medical personnel when they are treating infected patients or making contact with contaminated surfaces. Typical PPE commonly consists of gloves, goggles, a gown, a head cover, a face mask and respirator, shoe covers, and a face shield, which are regarded as a general safety precaution for infection prevention. The effectiveness of PPE is influenced by proper selection of PPE (selection of the type of mask, for example), appropriate usage of PPE (donning/removal), and proper disposal of PPE (*8*). Although recommendations regarding PPE are sometimes controversial, PPE is undoubtedly emphasized and recommended during pandemics involving infectious respiratory diseases. During the COVID-19 pandemic, all frontline medical personnel were required to know appropriate methods of using PPE in clinical settings. Nonetheless, appropriately donning/removing PPE is quite complex and is poorly understood by most new medical personnel. John *et al*. reported that only 39% of untrained medical students can select the correct sequence of donning/removing PPE (*9*). Wilder-Smith *et al*. reported only 34% of medical personnel could correctly use PPE (*10*). Mitchell *et al*. reported that inappropriate donning/removing PPE is a significant risk factor for development of NIs (*11*). Conversely, proper use of PPE may help to reduce NIs (*12*). A point worth noting is that during an infectious respiratory disease pandemic, and especially in the early stages of the pandemic, inappropriate use of PPE might be dangerous, or even life-threatening. Flaws in donning/removing PPE can cause pathogen transmission and lead to NIs (*13*). Accordingly, effective and evaluable training in using PPE is indispensable for medical personnel. The conventional centralized training model has many limitations, such as the time and effort it takes and limited efficiency, so it cannot ensure all trainees learn/understand proper skills of donning/removing PPE. In this regard, many optimized training models have been proposed, such as the information–motivation–behavioral skills (IMB) model. Recently, Song *et al*. used the IMB model to improve the skills of donning/removing PPE. They found that a group receiving an IMB model-based intervention had better performance in terms of self-efficacy and qualified usage of PPE among medical personnel during the COVID-19 pandemic (*12*). However, this model also has limitations. Noticeably, the entire process of donning/removing PPE cannot be monitored and supervised in real time. Flaws in the process could not be identified and corrected in a timely manner. This might serve as a Trojan horse for NIs. To ensure all personnel can properly don/remove PPE both in training and also in clinical practice, the current authors developed a novel artificial intelligence-based training and monitoring system (AITMS). The aim was to develop a newer system that would help to improve the donning/removing of PPE and reduce the frequency of NIs, ultimately helping to improve the clinical outcomes and QOL of inpatients. The current pilot study was designed to verify the effectiveness of the AITMS in preventing NIs.

2. Materials and Methods

2.1. Components of the AITMS

The AITMS consists of a camera with a voice broadcasting feature, a backend administration system on the cloud, a smartphone app, and an AI-based surveillance/training terminal for donning/removing PPE and hand hygiene (these are denoted as "behaviors" in the following sections). The terminal consists of an AI on a local computer, along with a large screen (for displaying correct "behaviors" or serving as a human-computer interface) with voice packets (for voice guidance and error prompts) (Figure 1). The AITMS has two working modes, namely, AI-based protective equipment surveillance mode (AIPESM) and AI-based training mode (AITM), which can be simply selected *via* the smartphone app or the terminal (Figure 1). The AIPESM is used to monitor a member of medical staff's "behaviors" and detect flaws in practice, whereas the AITM is used to training personnel if they need training. The AITM can certainly be used to solely train new personnel.

2.2. Definition of "standardized target behaviors (STBs)"

STBs were defined as per China's Technical Guidelines on Prevention and Control of Novel Coronavirus Infection in Medical Institutions (third edition) (*14*), including 7 steps of donning and 15 steps of removing protective equipment.

2.3. Generation of a dataset

Data collection sites were established where medical personnel don/remove PPE. All the normative "behaviors" performed by a group of skilled personnel were recorded by a camera based on the Kinect technology. Every frame of the video was recorded and preprocessed. The size of the video frame was

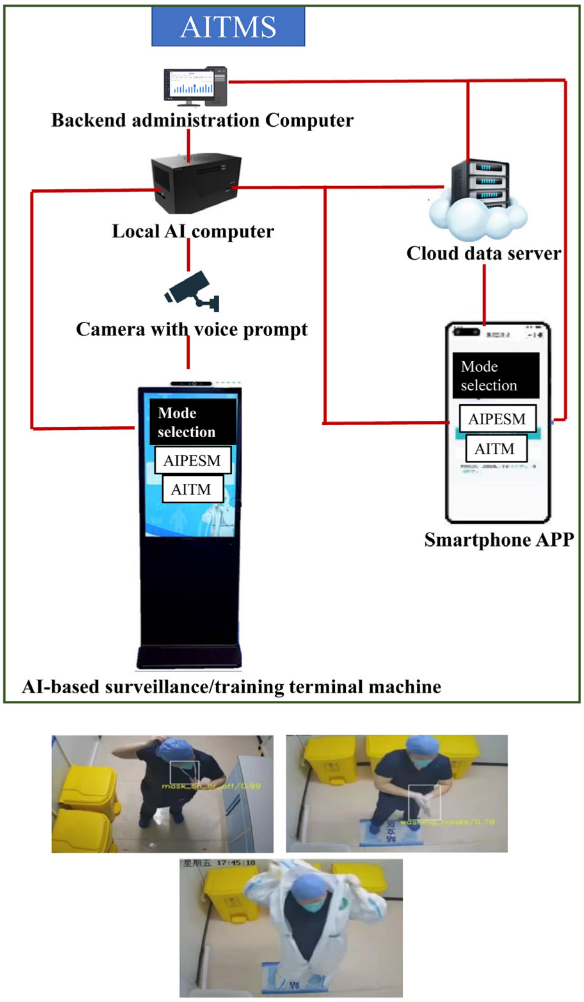

Figure 1. A diagram of the artificial intelligence-based training and monitoring system (AITMS). AI: Artificial intelligence; AITMS: artificial intelligence-based training and monitoring system; AIPESM: AI-based protective equipment surveillance mode; AITS: AI-based training mode (AITM); APP: application; PPE: personal protective equipment.

normalized. Then, the types of behaviors involved in donning/removing PPE and hand hygiene that need to be marked (target behaviors) and the marking rules were determined. Behaviors in all frames of preprocessed images were subsequently marked. The marked data were approved both by the AI and manually to avoid missing or wrong marks.

2.4. Training and creating an AI model to evaluate STBs in images with machine learning

After all of the images were marked, the system automatically identified marked images and label files, which were subsequently divided into a training set and a test set at a ratio of 9:1. The AI used the training set to train the model, and the model performance was checked using the test set. The models were continuously optimized by adjusting the parameters and tests. On the basis of the results of model testing, samples were added when target behaviors or backgrounds were readily misdetected. These processes helped to improve the accuracy to reach the anticipated standard. Ultimately, an AI model to evaluate STBs in images was successfully created.

2.5. Application to actual processes

Once the data accuracy reached the standard, the AI model was applied to actual processes to make precise adjustments and to facilitate optimization. The system was used in locations where PPE is donned/removed. We ensured that all the "behaviors" of the testees (hand washing, donning/removing one's mask and protective suit, *etc*.) could be clearly detected. The current AI model to evaluate STBs in images had satisfactory accuracy, particularly at detecting the behaviors of donning/removing one's protective suit. In addition, this system enabled the AI model to improve its accuracy by continuous self-learning during actual use.

2.6. Scenarios for application

The AIPESM is activated to monitor clinical routine tasks of medical personnel. When medical personnel step into the designated area, he or she should don/remove PPE and perform hand hygiene following the guidance of the voice prompt. The surveillance camera is activated and it performs real-time surveillance while the "behaviors" are performed. All the human postures and limb motion trajectories are captured and analyzed based on Kinect technology. All the "behaviors" of the testees are compared to the STBs in images evaluated by the AI model, including the sequence of behaviors, range, and angle. A "correct/incorrect" behavior is defined by the AI model according to its conformance to the STBs. Once an "incorrect behavior" occurs during the process, the camera captures this flaw and then submits it to the AI on the local computer. The AI system will judge whether this behavior is "incorrect". Once a flaw is confirmed, the system will remind the person to correct his or her behavior *via* the voice prompt. Only when a behavior is in line with the "STB" is it deemed to be a "correct behavior", and the person can continue with the process. If needed, experienced backend staff can also help personnel. Once a person is identified as needing training, he or she may choose to use the AITM. The required training course (donning a gown, for example) can be selected *via* the smartphone app. The theoretical knowledge and a video of the STB video will be displayed *via* the large screen to guide the person so that he or she can perform the "correct" behavior. The camera captures the person's movements during training, the system corrects his or her mistakes *via* the voice prompt, and it evaluates the person's performance during training. Other than in a clinical setting, the AITM can also be used to train new personnel. Training, real-time evaluation/corrections, and administration of a final examination can be performed. Certificates will be issued along with the complete training files after the trainee passes the theoretical and practical exams. The files can be synchronized in the main computer and mobile terminal. Analysis of the obtained data will help to continuously optimize the training programs as well as the algorithms.

2.7. Data acquisition and analysis

The AITMS was introduced at this Hospital starting in February 2020. When surveillance started (from February 7, 2020 to February 13, 2022), none of the personnel had ever been trained by the AITMS. The accuracy rate automatically recorded by the system was recorded as the non-AITMS rate. From November 20 to 26, 2022, almost all of the personnel were trained with the AITHM. The accuracy rate at that time was recorded as the AITMS rate. Data on the frequency of NIs from 2019 to 2022 at this Hospital are available on the National Medical Institution Infection Surveillance System of China (*https://cniss.yygr.cn/*). The software SPSS (v24.0.0, IBM, USA) was used for statistical analysis. A chi-square test was used to compare rates. $p < 0.05$ was considered to be a statistically significant difference.

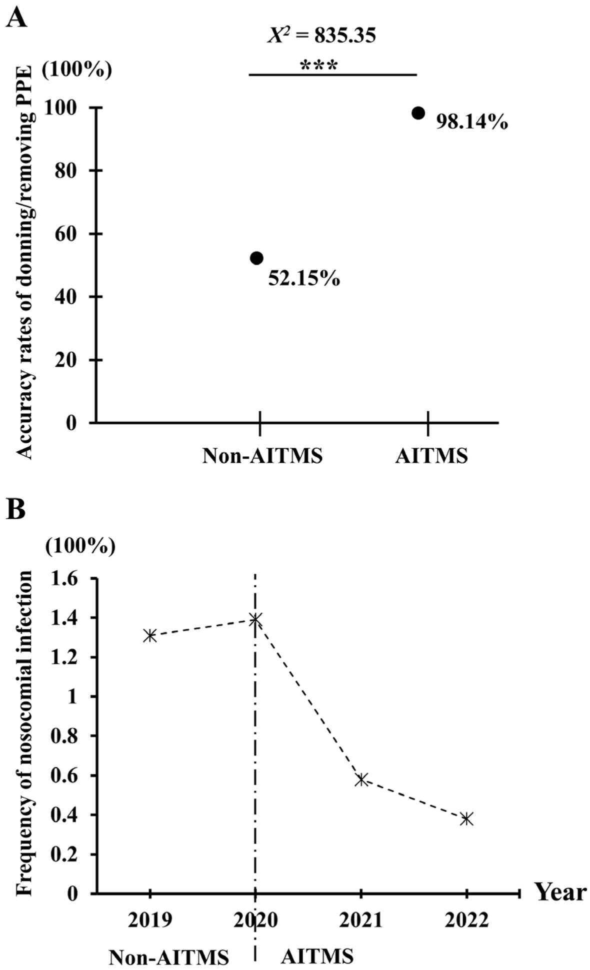

Figure 2. Effectiveness of using the AITMS. (A). Using the AITMS significantly improved the accuracy rate of donning/removing PPE. **(B)**. Using the AITMS markedly reduced the frequency of NIs. The AITMS was not used during the two years on the left while it was used during the two years on the right. The decline in nosocomial infections is evident despite the COVID-19 pandemic in 2021 and 2022. AITMS: artificial intelligence-based training and monitoring system; PPE: personal protective equipment. *** means $p < 0.001$

3. Results and Discussion

Figure 2A shows the accuracy rate before and after training with the AITMS. From February 7, 2020 to February 13, 2022, a total of 163 personnel had finished the evaluation, and their accuracy rate was 52.15% (85/163, non-AITMS rate). From November 20 to 26, 2022, the accuracy rate was 98.14% (3,159/3,219, AITMS rate). These data indicate that the accuracy rate of donning/removing PPE significantly increased as a result of using the AITMS (98.14% *vs*. 52.15%, $\chi^2 = 834.35$, $p < 0.001$). Indeed, after training with the AITMS, most of the medical personnel could properly don/remove PPE (Figure 2A). Interestingly, the frequency of NIs also decreased accordingly. As shown in Figure 2B, the frequency of NIs was 1.31% in 2019 and 1.39% in 2020 before use of the AITMS; after use of the AITMS, the frequency decreased sharply to 0.58% in 2021 and 0.38% in 2022. Hence, use of the AITMS helped to reduce the frequency of NIs even though the COVID-19 pandemic struck in 2021 and 2022.

This pilot study preliminarily verified the effectiveness of the AITMS. Use of the AITMS eventually reduced the frequency of NIs as the accuracy rate of donning/removing PPE improved. This study suggested the key role of using PPE in controlling and preventing NIs. Data preliminarily proved that appropriate donning/removing PPE may help to prevent the development of NIs In addition, the newest computerized technologies, such as AI, machine learning, big data, and mobile Internet (*15*), have proven to be useful in controlling and preventing NIs. The current results are in line with those of previous analogous studies (*16,17*). These findings should help to formulate a strategy against NIs in the future. In the future, more rigorous verification will be performed to provide robust evidence regarding use of the AITMS to reduce NIs.

Using AI-based technology to control and prevent NIs is a novel idea. Here, this novel AITMS has proven to be effective in both routine clinical practice and training. The two-mode design allows this system to be applied in multiple scenarios, such as routine surveillance, real-time correction of inappropriate "behaviors", timely training on demand, systematic training for new personnel, and evaluation and examination of trainees. Using this AI-based system markedly improved the efficiency of surveillance and training. This system can ensure that medical personnel and trainees actually understand the skills of donning/removing PPE. Compared to conventional methods, the SITMS can save manpower and time, so it is particularly good in scenarios involving the outbreak of a certain infectious disease when numerous new personnel need to be rigorously trained in a short amount of time. It can also serve as a routine surveillance system in a hospital or department when PPE is often used. However, AI technology is far from flawless. There are still technological limitations so far: The recognition accuracy is affected by many factors, such as the camera angle, speed of human movement, and the degree to which movement is standardized (*18*), and this is particularly true for the recognition of fine movements (*19*). The efficiency of self-learning is still too limited (*20*). These limitations might potentially cause errors in the recognition of movements, so they should be addressed in future research and development. Even though AI cannot completely take the place of clinicians right now, the value of AI technology cannot be ignored. It can help to continuously optimize the strategies against NIs, including devising more reasonable "STBs", simpler but efficient training processes, and a more friendly human-computer interface. The current finding should help to achieve medical care with "no harm and no infections" in an era of constantly emerging infectious diseases (*21*).

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