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Original article

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Abstract

Background

Current procedures for effective personal protective equipment (PPE) usage rely on the availability of trained observers or 'buddies' who, during the COVID-19 pandemic, are not always available. The application of artificial intelligence (AI) has the potential to overcome this limitation by assisting in complex task analysis. To date, AI use for PPE protocols has not been studied. In this paper we validate the performance of an AI PPE system in a hospital setting.

Methods

A clinical cohort study of 74 healthcare workers (HCW) at a 144-bed University teaching hospital. Participants were recruited to use the AI system for PPE donning and doffing. Performance was validated by the current gold standard double-buddy system across seven donning and ten doffing steps based on local infection control guidelines.

Results

The AI-PPE platform was 98.9% sensitive on doffing and 85.3% sensitive on donning, when compared to remediated double buddy. On average, buddy correction of PPE was required 3.8 ± 1.5% of the time. The average time taken to don was 240 ± 51.5 seconds and doff was 241 ± 35.3 seconds.

Conclusion

This study demonstrates the ability of an AI model to analyse PPE donning and doffing with real-time feedback for remediation. The AI platform can identify complex multi-task PPE donning and doffing in a single validated system. This AI system can be employed to train, audit, and thereby improve compliance whilst reducing reliance on limited HCW resources. Further studies may permit the development of this educational tool into a medical device with other industry uses for safety.

Keywords: artificial intelligence, personal protective equipment, healthcare worker, pandemic, infections, patient safety

Background

The unprecedented coronavirus disease 2019 (COVID-19) pandemic and surge in nosocomial infections has created a space for digital innovation to assist in improved patient and health care worker (HCW) safety. The correct use—both donning and doffing—of personal protective equipment (PPE) is an essential barrier protection for individual HCWs to protect them from infection. Standard PPE use requires a trained observer 'buddy' to ensure correct use and to remediate contamination. Failures in this process, particularly in doffing, have been studied, with over a hundred failure modes documented.[1] The buddy system also diverts valuable HCW resources from patient care.[2] Buddies are not always available, especially during a pandemic, and guidelines alone do not guarantee compliance, with no current standard compliance PPE checks.[1–3] Artificial intelligence (AI) is a valuable tool that can be used to improve safety of care, reducing harm, leading to improved patient outcomes and healthcare saving.[4]

PPE (including gloves, gown, mask, eyewear, hat) remains an essential part of the individual healthcare worker armamentarium against the evolving COVID-19 strains and the inevitable 'next' virus; however, it must be used effectively.[2,5–7] The pandemic has repeatedly shown health services becoming overwhelmed.[8] The influx of COVID-19 patients, additional to regular patient volumes, highlights a critical need to protect HCWs, thereby maintaining adequate staffing levels for patient care and preventing pathogenic spread. During the current period of widespread Omicron variant transmission, essential HCWs are expected to return to work and may be asymptomatic COVID-19 positive. Through the ages humanity has had many infectious disease challenges: bubonic plague, polio, Ebola, and now COVID-19, with solutions—quarantine, vaccines, and PPE—evolving in response. During the Ebola virus disease outbreak in 2014, HCWs were 30 times more likely than were non-HCWs to become infected, and more than 500 HCW died.[9,10] During the early phase of the COVID-19 pandemic (to May 2020), there were 152,888 HCW infected in 130 countries, with up to 17,000 HCW dying, according to Amnesty International.[8] With more availability and effective use of PPE, COVID-19 morbidity and mortality might have been reduced in major centres, resource-limited and remote areas.

Simulation in medical/healthcare worker training

In medical education and training, simulation is a widely-employed technique. Simulations enable users to experiment with different scenarios and improve their skills in a safe environment prior to real-world patient handling.[11] Simulations are particularly useful for upgrading competence in managing uncommon, but potentially fatal problems, without exposing HCWs and patients to risk.[12] Moreover, simulations provide an effective platform for active learning and mitigation of risk. Active learning has been shown to increase motivation to learn, improve knowledge retention, deepen understanding, and instil positive attitudes towards the subject being taught.[13]

AI in safety training

Adverse events related to unsafe care represent one of the top ten causes of morbidity and mortality worldwide, with up to a third of such events being preventable.[4] One major area is healthcare associated infections. AI-enabled systems already can be used to deliver simulation-based safety training to HCWs and to improve adherence to existing safety protocols; for instance, in real-time hand hygiene (HH) alerts in the outpatient setting using sensors.[14] We developed an AI-PPE donning and doffing protocol for training HCWs, with an emphasis placed on using appropriate PPE and on compliance with infection control precautions. The use of real-time optical classifier analysis allowing immediate feedback via SMS or email, and remediation of inappropriate PPE use or potential contamination.

Methods

Study design and participants

This clinical cohort validation study was conducted at a 144-bed University teaching hospital in the Sydney metropolitan area. All participants were HCWs who were voluntarily recruited by convenience sampling whilst on site in the regular work environment at Macquarie University Health Facilities. Demographic data was collected on age, gender, occupational role as a subcategory of HCW (nursing, medical students, physicians, surgeons, laboratory staff and administrative staff), previous PPE experience, race, and location of PPE assessment to better understand factors affecting AI system performance.

Inclusion criteria: Participants were 21–60 years of age and able to complete the donning and doffing process. Basic HH online modules were previously completed by participants, as correct PPE donning and doffing requires multiple HH steps.

Exclusion criteria: Participants were excluded if unwell, symptomatic, or physically unable to perform all steps. We did not restrict study participants based on the extent of PPE experience or knowledge.

The platform was run as a 'guided' step-by-step donning and doffing educational tool for basic training of the novice or infrequent user, ensuring each step in the process was correctly and sequentially completed. The internal informatics scored the process and provided a compliance check of basic training.

The AI system was configured to correctly detect seven donning and ten doffing steps along with an end-state review step after donning and before doffing (donning step 8 and doffing step 1 on Figure 1). These steps will have an important role in future iterations of the software. The purpose of the additional end state image classifiers in the AI system was to allow the platform to audit and check compliance of the participant at the end state of donning and before doffing, a unique feature of this system which caters for high volume experienced use. The steps replicate local patient safety agency guidelines and are summarised in Figure 1.[15,16] The modular system enables steps to be removed as PPE guidelines are modified, for example footwear. Competencies for HH and PPE training were assessed by completion of respective NSW Health training modules.

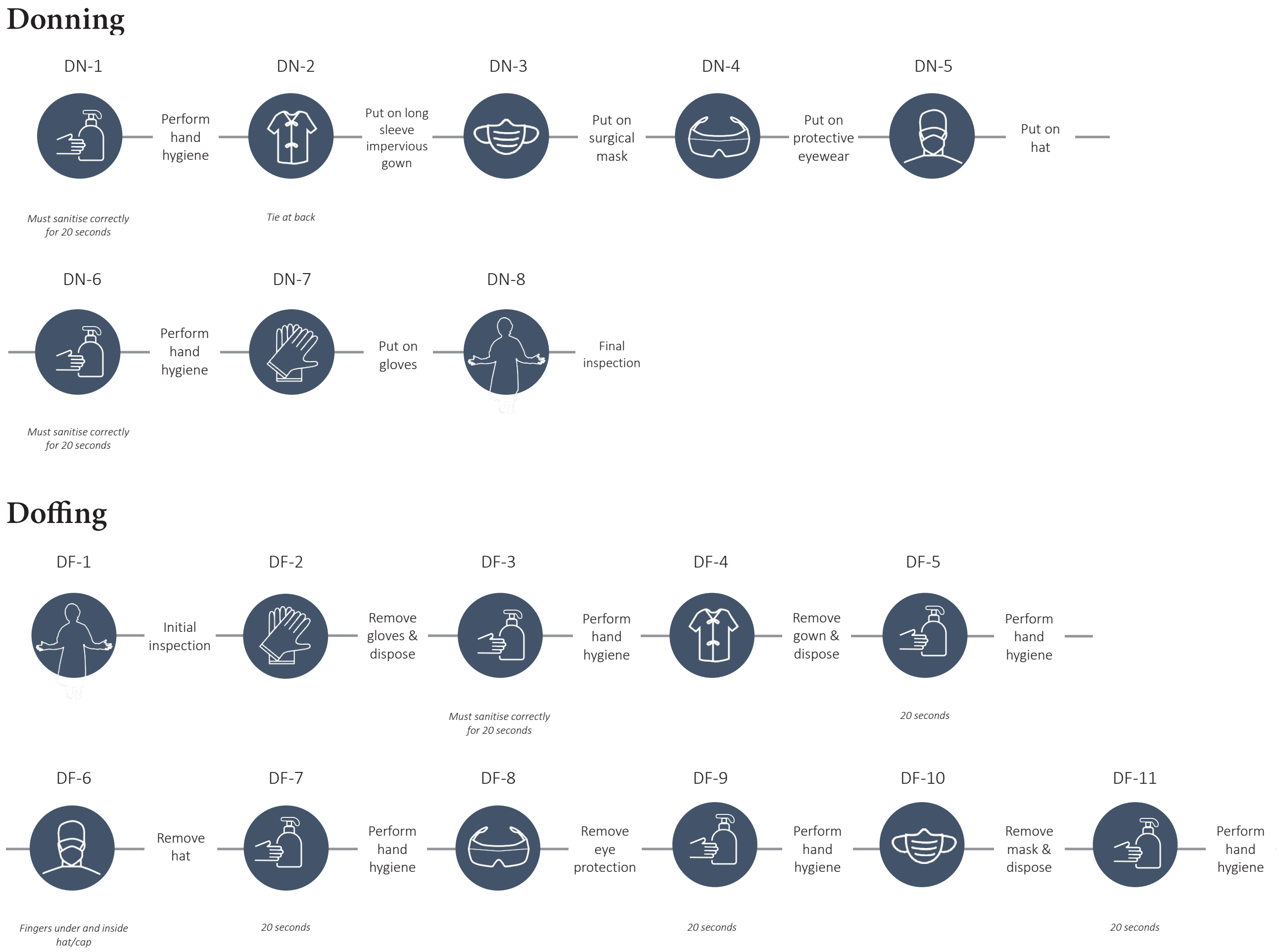
Protocol

For each participant, the study and AI-PPE system was discussed with a study investigator and informed written consent was obtained. Participants received an overview on donning and doffing, to the level available on the NSW Health system.[15,16] A training account was then made on the system for the participant for a step-by-step report and personal record of their PPE session. Following this, they commenced AI-guided PPE donning and doffing (Figure 1) under the supervision of two proficient experienced buddies. Facial recognition and voice prompts were used to allow for hands-free log in and direction of the AI platform.

The AI system runs a computer application on the device and data is hosted by a web-based platform using the built-in camera, stationed between the participant's waist and chest height, with the participant's face approximately in the middle of the screen. Where possible, the background was well-lit. Different locations were used with measures taken to ensure lighting and environment were comparable. PPE was provided on an adjacent trolley. Standard PPE items used were: light blue netted hat; light blue face mask; light blue gloves; light blue gown; and clear safety goggles. The platform uses proprietary SXR 'classifiers' which are optical AI recognition algorithms specific to each piece of PPE and its appropriate application.

Experienced PPE buddies were present in the same room, independently scoring and not blinded to the AI platform. Buddy intervention occurred if PPE was not present, was defective,

Figure 1: Steps assessed by the AI-PPE platform: donning steps DN-1 to DN-8 on entering a room; and doffing steps steps DF-1 to DF-11 on exiting (as adapted from the New South Wales Clinical Excellence Commission and National Health and Medical Research Council)[15,16]



or was worn in a way that might risk infection. Where buddy intervention was required, a brief descriptive note was recorded. Buddies marked a 'pass' if the step was correct and in the right order as instructed. AI assessment took place after buddy intervention and correction. Thus, in this first instance using two buddies, we assume the PPE to be appropriately protective; the goal here is to assess accuracy of the AI platform against this 'gold standard'. For future studies with only one buddy, the end state image (step DN-8, Figure 1) can be used to challenge the 'gold standard'.

We used a 2 × 2 table to evaluate AI-PPE outcomes (Table 1). The application either detects appropriate PPE use, 'PPE detected', or does not, 'PPE not detected'. The PPE usage can be either 'correct' (protective) or 'wrong' (at risk of contamination).

Therefore, we evaluate outcomes in the following way (Table 1):

Table 1: Summary of approach to AI scoring interpretation and assessment[a]

		PPE usage	
		Correct	**Wrong**
AI function	**Detected**	Pass	Fail
	Not detected	Fail	(Pass)

a AI function is qualified against PPE usage with four possible outcomes. 'Pass' events where 'wrong' PPE is 'not detected' are in parentheses, as this study focuses on post-buddy-remediation assessment, thus PPE use is assumed to be correct unless otherwise stated.

The AI application has functioned accurately ('pass') when either

- the AI detects appropriate PPE use and the PPE is used correctly (protective/ safe)
- the AI does NOT detect appropriate PPE use and the PPE use is wrong (at risk of contamination/unsafe).

The AI application has failed to function accurately ('fail') when either

- the AI detects appropriate PPE use and the PPE use is wrong (at risk of contamination)
- the AI does NOT detect appropriate PPE use and the PPE is used correctly (protective).

In this first assessment the double buddy intervention is assumed to produce correct PPE use, allowing us to assess the AI performance to this current gold standard. Thus, there are assumed to be no 'pass' instances of type ii unless specifically stated. (In future assessments, with AI remediation capability, the buddy system can also be assessed as if it is fallible.)

Time was measured from step DN-1 to end state image (DN-8) for donning and from initial inspection (DF-1) to end of final hand hygiene (DF-11) for doffing and recorded internally.

Outcome measures and statistical analyses

The primary outcome was accuracy of AI scoring ('pass' events/total %) against double-buddy-corrected reference (assumed to be 100% accurate) for donning and doffing of PPE containing steps gown, mask, eyewear, netted hat, and gloves. Although the platform guides participants through all the steps including hand hygiene, this study focuses on evaluating PPE detection.

The secondary outcomes were sensitivity, buddy assistance requirements for each step, and time taken to don and doff PPE.

AI detection for donning and doffing was recorded internally on the SXR AI program (Sydney NSW, Australia) and exported to Microsoft Excel (Redmond WA, USA). The instances where the buddy had to intervene to ensure PPE use was appropriate were also recorded. Statistical analysis was performed using GraphPad Prism 9 (San Diego CA, USA) and SPSS (Armonk, NY, USA).

AI accuracy was determined as the percentage sum of 'pass' events (Table 1) among total events. Statistical significance was assessed through exact binomial and McNemar's tests ($\alpha = 0.05$) of a 2×2 contingency table with AI assessment against buddy post intervention standard as exposures, and with 'pass' and 'fail' as outcomes. Overall values for donning and doffing were calculated as the sum of events of each outcome type across all steps: gown, mask, eyewear, hat and gloves. These were then assessed using exact binomial and McNemar's tests. Donning and doffing timing was recorded internally on the AI-PPE application.

Ethical approval

This study was reviewed and approved by the human research committee at Macquarie University (Sydney, Australia; HREC 5590).

Results

Seventy-four HCWs were recruited for this study. Demographic data are summarised in Table 2.

Primary outcome and overall results

Sensitivity of the AI-PPE platform to the remediated double buddy standard was 98.9% overall for doffing ($p = 0.125$ by exact binomial) and 85.3% overall for donning ($p < 0.01$),. The overall sensitivity for donning was 85.3% for the AI-PPE platform ($p < 0.01$), resulting from significant differences against the double-buddy-remediated standard in donning mask,

Table 2: Summary of demographic data[a]

	Category	n (%)
Sex	Male	33 (44.6)
	Female	41 (55.4)
Age	21–30 years	33 (44.6)
	31–40 years	28 (37.8)
	41–50 years	8 (10.8)
	51–60 years	5 (6.7)
Occupation/role	Laboratory staff	31 (41.9)
	Physician	3 (4.1)
	Junior medical officer	9 (12.2)
	Medical student	14 (18.9)
	Nurse	6 (8.1)
	Administration staff	8 (10.8)
	Surgeon	3 (4.1)
PPE and hand hygiene (HH) training	PPE and HH	71 (95.9)
	HH only	3 (4.1)
Ethnicity	East Asian	12 (16.2)
	South Asian	11 (14.9)
	Caucasian	37 (50)
	Middle Eastern/Mediterranean	10 (13.5)
	Afro-Caribbean	1 (1.4)
	Polynesian	3 (4.1)

a Total n = 74, all with complete demographic data.

eyewear and gloves. Averaged across donning and doffing, the sensitivity of the AI platform to the double buddy remediation was 92.3%.

The buddy correction was required in 3.8 ± 1.5% of steps (Table 4), with more correction required for donning steps, at 7.1 ± 2.0%, than for doffing steps at 0.5 ± 0.5%. There were ten instances of lab staff declining to wear a hat, as it was not required on their local guidelines. Thus, these were not included as corrections. The AI-PPE correctly did not detect PPE in all these cases. These were the only 'pass' instances due to correct non-detection for 'wrong' PPE use in our study.

Donning

For donning of mask and eyewear, there was a significant difference between AI scoring and buddy assessment ($p < 0.01$), with the result for donning of gloves also approaching statistical significance ($p = 0.02$ and 0.01 by the exact binomial and McNemar tests respectively) (Table 3). The AI scoring for donning mask was consistent with current buddy standard in 64.9% of cases. We also observed a high buddy assistance requirement in this step (14.9%). This was generally for inadequate moulding at the nose bridge, for inadequate extension of the

Table 3: Summary of results for primary outcome (AI passed %) and sensitivity values

Category	PPE item/ action	Step	AI passed (%) (n = 74)[a]	Sensitivity (%)	*p*-value[b]	
					exact binomial	McNemar
Donning	Gown	DN-2	87.8	90.3	0.18	0.10
	Mask	DN-3	64.9	64.9	< 0.01	< 0.01
	Eyewear	DN-4	75.7	77.8	< 0.01	< 0.01
	Hat[c]	DN-5	93.2	93.7	0.38	0.18
	Gloves	DN-7	86.5	87.7	0.02	0.01
Doffing	Gloves	DF-2	100.0	100.0	N/A	N/A
	Gown	DF-4	98.6	98.6	1	0.32
	Hat	DF-6	97.3	97.3	0.50	0.16
	Eyewear	DF-8	100.0	100.0	N/A	N/A
	Mask	DF-10	98.6	98.6	1	0.32
Overall	Donning	DN-1 to DN-8	84.3	85.3	< 0.01	< 0.01
	Doffing	DF-1 to DF-11	98.9	98.9	0.125	0.05
	All steps	—	91.6	92.3	< 0.01	< 0.01

a 'AI passed %' refers to the proportion of assessed events that were correct detections of protective PPE. In all steps except 'donning hat',[c] PPE was assumed to be correct as verified by double buddy.

b The p-values indicate results for each step with exact binomial and McNemar tests, for α=0.05. N/A: not applicable.

c In the case of 'donning hat', 'AI passed' events also include ten instances of non-detection of PPE when PPE was absent.

mask to cover the chin, and/or for instances in which the donned mask was worn at the edge of or below the nose.

The donning eyewear classifier had a sensitivity of 77.8%. We observed that good PPE was missed by the AI at a much higher rate in laboratory and simulation centre settings, at 29% and 21% respectively, than on the ward, where it was missed 4% of the time. Of note, the former environments had bright ceiling lights, whilst the ward environment was generally more dimly lit.

In our study, the donning hat classifier had the highest sensitivity of 93.7% (p = 0.38).

Doffing

There were no major discrepancies between AI assessment and double buddy remediated standard for doffing. Errors were all cases of incorrect detection of PPE when PPE had been removed. There were no instances of retained PPE missed by the AI. Thus, PASS rate equalled sensitivity (Table 3). Overall, the AI demonstrated excellent capacity to recognise doffing and identify absence of PPE at each step.

Timing

We examined the time taken to don and doff. Mean ± standard error of mean (SEM) time taken to don was 4 minutes 0 seconds ± 51.5 seconds, inclusive of all necessary hand hygiene steps, whilst mean time to doff was very similar at 4 minutes 1 seconds ± 35.3 seconds.

Discussion

Having a trained buddy to monitor PPE compliance is important for health care safety. The

Table 4: Percentage of participants requiring buddy intervention to ensure protective PPE, and noted reasons for requiring intervention[a]

Category	PPE item/action	Step	Buddy assistance required (%)	Reason for requiring assistance[b]
Donning	Gown	DN-2	6.8	• Gown not tied • Thumbs not securely placed through holes
	Mask	DN-3	14.9	• Not fully extending mask below chin • Not moulding nose bridge • Mask worn at edge of/below nose
	Eyewear	DN-4	5.4	• Incorrect detection of spectacles • Claiming eyewear not required because spectacles present
	Hat[c]	DN-5	4.1	• All hair not contained • Not routinely worn by some lab staff
	Gloves	DN-7	4.1	• Worn under gown • Passed by AI prematurely
Doffing	Gloves	DF-2	0	N/A
	Gown	DF-4	0	N/A
	Hat	DF-6	2.7	Missed instruction and did not remove hat in time
	Eyewear	DF-8	0	N/A
	Mask	DF-10	0	N/A
Overall (mean ± SEM)[d]	Donning	DN-1 to DN-8	7.1 ± 2.0	N/A
	Doffing	DF-1 to DF-11	0.5 ± 0.5	N/A
	All steps	—	3.8 ± 1.5	N/A

a n = 27.

b N/A: not applicable.

c For 'hat', 13.5% of participants (lab staff) chose not wear hats due to local lab PPE guidelines. The platform correctly avoided detection in all these cases, and so these instances have been marked as 'AI passed'.

d SEM: standard error of mean.

gold standard of double buddy human resource allocation is not always practicable. To date the literature focusses on doffing, where much of the self-contamination risk is reported.[1,17] There is very little literature on donning. Our paper provides some contribution to this, as we expect both to be monitored to provide safest PPE setup.

Overall, our results demonstrate that the AI platform provides excellent sensitivity for doffing, at 98.9%, with a statistically non-significant difference to a double buddy standard. This is the major area to date of literature focus in PPE use. Donning using the AI platform has a sensitivity of 85.3%. There is the potential significant psychological effect of an onsite double buddy, which was not characterised, but which may have influenced buddy assistance requirements.

At this stage, our goal was to determine the capacity of classifiers to correctly identify applied PPE to a double buddy standard, and to identify completion in the correct sequence. For this purpose, donning classifiers can be made much stricter, unlike doffing classifiers. This in part explains the overall difference in accuracy observed between donning and doffing. Since the mask is one of the most-used pieces of PPE, we felt it was prudent to challenge the platform with strict classifiers, and this is reflected in the results seen. Interestingly, buddy remediation rates were also high for mask donning, which supports an area for HCW upskilling.

Similarly, there was a high fail rate for eyewear. This may be explained by a combination of strict donning classifiers under bright lighting. Bright ceiling lighting may have caused good PPE to be missed by reflections obscuring the borders of existing spectacle eyewear. Moreover, the laboratory and the simulation centre, both locations with bright ceiling lights, had high rates of undetected good PPE. Further study under controlled and measured lighting would be valuable.

The buddy intervention requirement prior to AI recognition is important to this study design. This requirement helps us understand the common errors that may be encountered in PPE donning and doffing, and suggests focuses for remediation steps for the AI. In our study, we noted that mask donning had a surprisingly high requirement for buddy correction. We have already attempted to make strict mask classifiers. This data reaffirms the importance of these efforts. In forthcoming studies, different masks such as N95 masks are being used, to assess and train the versality of the platform.

Buddies were not blinded to the platform, and were present in the same room; it is also possible that the AI detected risk which would have otherwise been missed by the buddy. We plan to explore this further in subsequent study designs.

We examined a range of demographic factors to better serve a diverse user group. Our cohort verifies the capacity for the platform to successfully guide donning and doffing for a range of race and age characteristics. Additionally, of the 74 participants 54% were female, which offers a good balance and approaches the 60–70% majority of the healthcare workforce who are female.[18] Racial bias can be a problem in AI-based software, as has been well described in the literature.[19] Strengths of this study include that we have actively attempted to reduce the influence of factors that would contribute towards racial bias during the training of this platform. We have a variety of participants recruited in this study reflective of our multicultural population,[20] which for global applicability is essential. Participants of all included ethnic backgrounds were able to complete the assessment, though our study was not powered to assess statistical differences.

The timing of donning and doffing was consistent with expectations. Despite the increased number of 20-second hand hygiene steps involved in doffing, the mean times between donning and doffing were very similar. There is limited literature reported regarding donning and doffing times for the type of protocol used in this study. However, more extensive PPE protocols with head-to-toe body suits, as used during the Ebola outbreak and early in COVID-19 pandemic have recorded times for doffing alone of 6–7 minutes.[10,21] Our current data sets a reasonable baseline time for safe, standardised donning and doffing, contributing to the information around task diversion and potential time saving for human resource allocation where double buddy systems are relied upon.

Summary, limitations, and further directions

Given the state of communicable disease today and the trends with the latest COVID-19 strains, AI-PPE remains highly relevant and usable in an area of ongoing workforce shortage.[22] There are minimal operational limits with extensive applications for deployment into any workplace. As the pandemic has enabled upskilling of all workforces towards digital platforms and communication, this too can quickly, reliably and easily be integrated.[23,24] It can be used by all HCWs regardless of level in the hierarchy of the system, as demonstrated here, and has the potential to bypass language barriers. At an individual level, it has been developed into a ready-to-implement tool that provides feedback in real-time, without susceptibility to fatigue, human error or distraction from patient care. At an institutional level, it is a convenient accessible resource to assist auditing and documentation to shape research, safety policy and governance. We expect that research investigating the long-term clinical applicability of this model in real-world setting, including effects on patient and staff outcomes will be forthcoming, particularly in resource limited settings.

The 'learning' of the system after initial recognition training continues and accuracy improves. The system is still 'young' and the process of learning will be documented, with the intention to take the application from an educational and training platform to a possible medical device.

In future studies we aim to trial different PPE (colour, shape, brand including different masks such as N95) to help train versatility of the platform to locally-available equipment. Other work environments (aged care, quarantine, pharmaceutical industry and others) needing various PPE levels and scalability of PPE could benefit from this AI platform and classifiers.

Another important limitation of the study was that we did not assess for transitional errors; this will be explored in subsequent versions of the platform. This will be particularly important for contamination-free doffing.[17,25] This is a major area of our current work. For donning, classifiers will require continued refinement, particularly for mask, gloves and goggles.

Our further research will test this platform in differing lighting conditions and environments for further external validation. We tested the platform in the hospital wards, intensive care, clinics, simulation centres and laboratory setting. Future iterations of the platform could have lighting control integrated within the design, to achieve optimal and reproducible lighting conditions.

Finally, here we assess AI-PPE accuracy against post-remediation double buddy standard. This was necessary as the AI's accuracy has not yet been demonstrated. Future studies will compare pre-remediation AI assessment and then remediation against single buddy assessment and remediation, both under the validation of double buddy control.

Conclusion

The buddy system for PPE use is vulnerable in scenarios where human resources can be rapidly overwhelmed and staff furloughed, particularly in resource-limited and remote areas. AI-PPE has the potential to improve safety of care. This study presents a proof of concept of a new AI-PPE platform with real-time feedback to guide and assess donning and doffing of PPE. It demonstrates comparable accuracy to the current gold standard buddy system, along with the ability to integrate well into existing healthcare systems. This platform has been tested on staff with a range of visual characteristics with contributions from race, age and sex. Further work is required to perform optimally in a wide range of environments, and to address transitional errors. With ongoing refinement, it can be scaled to teach, train and audit HCW and other work environments needing PPE. This has implications for the implementation of PPE protocols in hospitals and other health care organisations to improve clinical practice and safety without diverting human resources. Convenient monitoring for compliance and trends allows for more targeted and effective governance of workplace and patient safety practices.

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