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Developing PPE management tools for use in a pandemic

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ABSTRACT
In early 2020, facilities across the United States and the world struggled to secure personal protective equipment (PPE) to protect their staff from COVID-19 during an international shortage. A sharp increase in PPE demand, coupled with dwindling supply, resulted in a need for strategies and tools to assist workplaces in calculating PPE burn rate and predicting future PPE needs. This study describes the development and potential use of a model-based approach for forecasting PPE demand for future pandemics or other disasters that require PPE. This simple-to-use modeling tool was developed to assist facilities that lack adequate PPE management systems, allowing users to track what PPE items they have on hand and how quickly their PPE supply is depleting. The modeling tool builds on previous efforts to understand PPE consumption, such as the Centers for Disease Control and Prevention's (CDC) Excel-based PPE Burn Rate Calculator and the National Institute for Occupational Safety and Health's (NIOSH) PPE Tracker Mobile Application. These tools were modifiable enough to use in a variety of settings, including healthcare, public safety, and correctional facilities, and were widely used for PPE management during the COVID-19 pandemic. The modeling approach described here can incorporate scenario-specific information into future PPE planning, rather than relying solely on historical consumption patterns. Hypothetical scenarios are presented to demonstrate the use of the tools. Results of this study indicate that PPE needs can be heavily influenced by local conditions. Predictive models for PPE needs may allow for increased efficiency, reduced waste, and improved worker protection.

KEYWORDS
Pandemic preparedness; personal protective equipment; PPE burn rate modeling; PPE management modeling

Introduction

Along with engineering and administrative controls, personal protective equipment (PPE) is a critical component of an infection prevention and control strategy to reduce exposure to pathogens in the workplace (Branch-Elliman et al. 2015; NIOSH 2015). In early 2020, the rapidly increasing number of suspected and confirmed coronavirus 2019 (COVID-19) cases in the United States resulted in an unprecedented demand for PPE items in healthcare facilities. To protect front-line healthcare workers (HCW) caring for patients with suspected or confirmed COVID-19, the Centers for Disease Control and Prevention (CDC) recommended a PPE ensemble that includes respirators or facemasks, eye protection, gloves, and gowns (CDC 2020). In light of the extraordinary demand, the U.S. and other countries experienced major PPE shortages and significant disruptions in the PPE supply chain (Bauchner et al. 2020). PPE-SAFE, an international survey of healthcare workers during the COVID-19 pandemic, collected responses from 2711 HCWs from March 30 to April 20, 2020 (Tabah et al. 2020). Results indicated that 52% of workers reported at least one piece of standard PPE item as not available. Thirty percent of respondents reported that single-use PPE items were washed or reused in response to shortages (Tabah et al. 2020). During the worst of the shortage, some facilities resorted to providing expired or improvised PPE to their HCWs, with little evidence to support the protectiveness of these items and causing many workers to fear for their safety. HCW strikes and protests were held across the country as HCWs expressed serious concerns about lack of necessary PPE and unsafe working conditions (Essex and Weldon 2021).

The CDC examined hospitalizations among healthcare workers associated with COVID-19 in the early

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months of the pandemic (Kambhampati et al. 2020). Of the 438 hospitalized HCWs included in their sample, 67.4% worked in occupations generally expected to have direct patient contact (Kambhampati et al. 2020). A metanalysis examined the prevalence of SARS-CoV-2 infection among HCWs reported in 46 studies (Gómez-Ochoa et al. 2021). The investigators calculated a pooled prevalence of infection to be 11% (95% CI; 7%-15%). While COVID-19 cases among HCW cannot be wholly attributed to workplace exposures, exposure to COVID-19 patients without proper PPE may have contributed to significant morbidity and mortality among HCWs.

As case numbers increased and resources were depleted, grassroots efforts to donate PPE from non-medical settings to healthcare facilities emerged while state governments encouraged local companies to shift to PPE production (Ranney et al. 2020). The Strategic National Stockpile (SNS), the United States' national repository of medical supplies, was activated and engaged over 180 private industry partners to supply and deliver PPE during the pandemic (ASPR 2021). Despite these efforts, healthcare facilities continued to face shortages well into the pandemic, particularly as non-hospital-based medical services began to resume business and reopen their practices to in-person patient care.

In May 2020, the CDC published strategies for optimizing the supply of PPE and equipment during the COVID-19 response based on facility surge capacity (de Perio et al. 2020). Surge capacity, which is a facility's ability to manage a sudden increase in patients, is categorized by CDC as conventional capacity, contingency capacity, or crisis capacity, depending on the influx of patients and the availability of PPE. To address contingency capacity needs, CDC strategies for optimizing PPE supply included administrative controls (e.g., decreasing the length of healthcare facility stay for medically stable patients and the suspension of annual respirator fit testing requirements) and changes to how PPE is used (e.g., extended use of N95 respirators). Before implementing these changes, CDC recommended that facilities take steps to understand their PPE inventory and supply chain, as well as how quickly they use their PPE, referred to as the PPE consumption rate or the PPE burn rate. Larger facilities often have systems in place to track their supplies, but smaller facilities and those adopting new PPE practices may benefit from tools to manage their PPE supply and calculate their PPE burn rate. Such tools may be particularly useful to small healthcare facilities and non-healthcare facilities (e.g., quarantine stations, correctional facilities, and Transportation Security Administration [TSA] screening operations) that may adopt PPE items that are not typically prescribed. This paper briefly describes how the CDC Burn Rate Calculator and the NIOSH PPE Tracker Mobile Application have been used to manage PPE supply. The development of a more sophisticated and generic Excel-based, modifiable mathematical model for estimating facility-level PPE needs for use in future pandemic scenarios is presented.

The CDC Burn Rate Calculator—Version 1 and Version 2

The CDC Burn Rate Calculator (https://www.cdc.gov/niosh/healthcare/hcp/pandemic/PPE-Burn-rate-calculator.html) utilizes a simple approach to estimate PPE needs (CDC 2025). Essentially, the tool works by creating an inventory of PPE items over several days and calculating the daily consumption using Microsoft Excel. The CDC Burn Rate Calculator was published online by the CDC in 2020 as a downloadable tool that allows users to input facility PPE inventory and track PPE supply over time. The Excel spreadsheet format allows the tool to be easily modified by end users to suit the specific needs of their facility. The spreadsheet is general enough to be used by a variety of workplaces and accommodates a variety of PPE types. Using the tool allows users to calculate true historic consumption of PPE by size and type; however, each facility is required to factor in potential increases in COVID-19 patient counts to estimate future PPE needs.

In the primary "Calculator" tab of the spreadsheet, users define the specific PPE items they plan to track and record daily (PPE supply). If users choose the option to enter the number of patients in their facility, the tool will provide the PPE burn rate per patient. Based on user input values, the tool calculates the PPE burn rate and number of days of PPE supply remaining, based on the following calculation logic:

$$\boldsymbol{Boxes\ remaining\ on\ dax\ X} = total\ inventory\ at\ the\ beginning\ of\ the\ day \tag{1}$$

$$\boldsymbol{Boxes\ used\ on\ day\ X} = boxes\ remaning\ on\ day\ (X+1) - boxes\ remaining\ on\ day\ X \tag{2}$$

$$\boldsymbol{Boxes\ used\ on\ day\ X, per\ patient} = (boxes\ remaining\ on\ day\ (X+1) - boxes\ remaining\ on\ day\ X)/(number\ of\ patients\ at\ the\ start\ of\ day\ X) \tag{3}$$

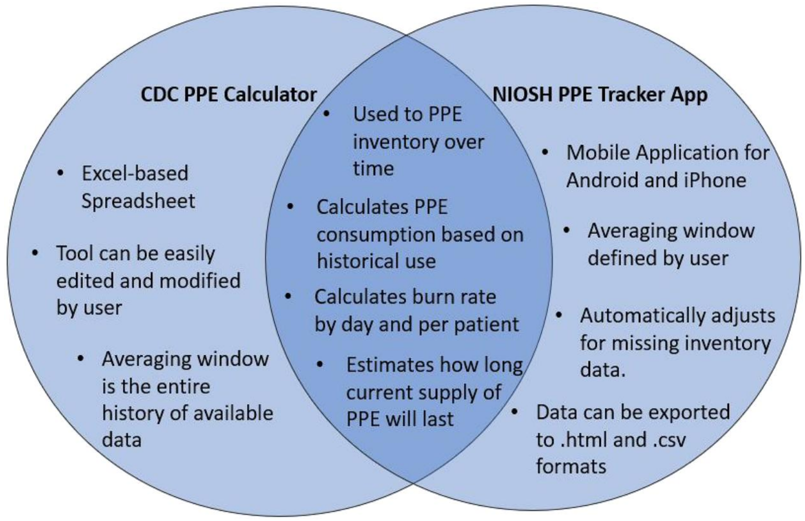

Figure 1. Comparison of the CDC PPE Calculator and NIOSH PPE Tracker App.

$$\boldsymbol{PPE\ burn\ rate} = \frac{\sum_{day\ 1}^{day\ N-1} boxes\ used\ per\ day}{N}, \tag{4}$$

$$where\ N = window\ length, in\ days$$

$$\boldsymbol{PPE\ burn\ rate, per\ patient} = \left(\sum_{day\ 1}^{day\ N-1} boxes\ used\ per\ day, per\ patient\right)/N,$$

$$where\ N = window\ length\ in\ days \tag{5}$$

$$\boldsymbol{Days\ supply\ remaining} = \frac{boxes\ remaining\ on\ day\ X}{PPE} / (PPE\ burn\ rate) \tag{6}$$

The "Graphs" tab of the spreadsheet allows users to visualize the consumption of their PPE supply over time with auto-populated graphs. Facilities can use this information to help anticipate future PPE needs and order supplies based on historical consumption rates.

Following the public release of the Burn Rate Calculator, CDC modified the tool to include the option to track up to 111 different PPE items and supplies, the ability to extend the number of days of tracking to 90 days, and the ability to add restocked inventory to the burn rate calculator. This version (Personal Protective Equipment Burn Rate Calculator Version 2) included improved ways to display PPE inventory data, including a display of the total PPE on hand, the expected number of days remaining supply will last, and the average burn rate of individual PPE items.

The CDC Burn Rate Calculator Version 1 did not account for restocking of PPE inventory. When using Version 1, the supply remaining on day X cannot be greater than the supply remaining on day (X-1). Version 2 includes modifications to accommodate restock.

The NIOSH PPE Tracker Mobile Application

The NIOSH PPE Tracker app (no longer available) was conceptually the same as the CDC Burn Rate Calculator but provides better usability features for mobile devices (reordering of screen features, improvements to drop-down menus and icons), and improved options to export data to .html and .csv formats. A comparison of the CDC Burn Rate Calculator and the NIOSH PPE tracker App is shown in Figure 1. Version 2 of the Burn Rate Calculator and the PPE Tracker App allow the user to add restocked items as follows:

$$\boldsymbol{Restock} = PPE\ items\ added\ since\ day\ X-1 \tag{7}$$

$$\boldsymbol{Boxes\ remianing\ on\ day\ X} = total\ inventory\ at\ the\ beginning\ of\ the\ day, including\ restock \tag{8}$$

$$\boldsymbol{Boxes\ used\ on\ day\ X} = boxes\ remaining\ on\ day\ (X+1) - boxes\ reamining\ on\ day\ X - restock \tag{9}$$

Table 1. Definitions of Excel model input variables.

Variable	Description
Percent of Population Fully Vaccinated (Percent_FullVax)	Percent of the population that has been fully vaccinated for COVID-19, defined as 2 wk after second dose in a 2-dose series, such as the Pfizer or Moderna vaccines, or 2 wk after a single-dose vaccine, such as Johnson & Johnson's Janssen vaccine.
Percent of population partially vaccinated (Percent_PartVax)	Percent of population that has been partially vaccinated for COVID-19, defined as the period from 2 wk after the first dose of a 2-dose series through 2 wk after the second dose of a 2-dose series, or 2 wk after a single-dose vaccine.
Full Vaccine Effectiveness (Full_Vax_Effec)	Effectiveness of vaccination 2 wk after second dose in a 2-dose series or 2 wk after vaccination of a single-dose vaccine.
Partial Vaccine Effectiveness (Part_Vax_Effec)	Effectiveness of vaccine after a single dose of a 2-dose series.
Total population (Tot_Pop)	Number of people living within the catchment area of the facility.
Positivity Rate (Pos_Rate)	Percent of susceptible population testing positive for COVID-19.
Hospitalization Rate (Hosp_rate)	Percent of COVID-19 cases that require hospitalization.
Percent of cases choosing facility (percent_case_choose)	Percent of cases that "choose" or are assigned this facility to be hospitalized.
PPE Items (PPE_Items)	Text list of PPE items used in the facility.
Standard Precautions PPE Ensemble (StdPr_PPE)	PPE used by HCW who are not expected to have contact with confirmed and/or suspected COVID-19 cases or infectious materials.
COVID-19 PPE Ensemble (COVID_PPE)	PPE used by HCW who are expected to have contact with confirmed and/or suspected COVID cases or infectious materials.
Number of health care workers (NumHCW)	Total number of HCWs (paid and unpaid) in the facility who may use PPE.

The following assumptions are used:

- Burn rates calculated will apply to the prior day and will only update after the current day's inventory is entered.
- The number of COVID-19 patients at the start of day X is approximately the number of COVID-19 patients being treated on day (X-1).
- Using the NIOSH PPE Tracker App, users can set the number of days used to calculate the burn rate. The averaging window is a span of N days defined in one of three ways:
    - the entire history of available data;
    - a specific date range;
    - the last N days (where N is a number defined by the user).

$N+1$ days of data are needed to calculate rates over a window length of N days.

Both the CDC Burn Rate Calculator and the NIOSH PPE Tracker Mobile App were originally released for use during the COVID-19 pandemic, but can be used to track PPE in a non-pandemic situation, as well.

Methods

Spreadsheet tool for predicting future PPE needs

Beyond tracking historical use of PPE like the CDC tools, simple predictive models that incorporate disease trends can be used to make better predictions about PPE needs on a facility level during future outbreaks, pandemics, or other disasters requiring PPE. To this end, a Monte Carlo simulation model was developed in Excel with the Oracle Crystal Ball plug-in. Data from a hypothetical hospital scenario (see Supplementary Materials Spreadsheet, Simulation 1 tab) were used to define model inputs. The model forecasts the number of confirmed or suspected disease cases that will be hospitalized in the facility, the expected number of HCWs who will have contact with confirmed or suspected disease cases, and the anticipated quantity of PPE items that will be needed. This model relies on calculations and assumptions based on local vaccination and positivity rates to forecast cases, but increasingly sophisticated epidemiological models could be used as well. To create the simulation model, data from the COVID-19 pandemic were used. The model could easily be adjusted to use data (e.g., vaccination and epidemiological data) from a future outbreak or pandemic.

The model assumes that all HCWs will need a set of standard precautions PPE daily, and that workers with patient contact will need additional PPE items. Items included in the standard precautions PPE and patient contact PPE ensembles can be modified by the user, but would typically contain some combination of gloves, gown, surgical mask, N95 respirator, and eye protection. The type and quantity of items included in each of the ensembles should be adjusted based on facility-specific PPE practices. Other inputs to the model relate to the characteristics of the catchment area of the facility—total population, vaccination rate, vaccine efficacy, local positivity rate, and hospitalization rate. Uncertainty and variability in input data were captured using Monte Carlo simulations. Distributions were assumed for variables for which exact values are not known, and thus, the model forecasts a range of possible PPE needs. The simulation used 2,500 runs of the model to give a probabilistic distribution of possible outcomes.

Model variables

The variables used in the model are described in detail in Table 1. As previously mentioned, data from the COVID-19 pandemic were used for the simulations. Percent_FullVax and Percent_PartVax represent the percentage of the population that is fully or partially vaccinated, respectively, based on whether individuals have received one or two doses of a two-dose vaccine (e.g., the Pfizer or Moderna vaccine during COVID-19) or a single dose of a single-dose vaccine (e.g., Johnson & Johnson's Janssen vaccine). Vaccine effectiveness of full and partial vaccination is captured with the variables Full_Vax_Effect and Part_Vax_Effect, respectively. Several research studies provide estimates for vaccine effectiveness, although this value should be modified based on the pathogen of concern and as new data emerge on changes in vaccine effectiveness over time and with new variants (Polack et al. 2020; Britton et al. 2021; Pilishvili et al. 2021; Thompson et al. 2021).

The variable Total Population (Tot_Pop) represents the number of people living in the catchment area of the facility. A catchment area population of 100,000 was assumed for the hypothetical facility. Positivity rate (Pos_Rate) is the fraction of diagnostic tests for the pathogen of interest (e.g., COVID-19 tests) administered that were positive for the pathogen of interest over a specified time window in the facility catchment area. In the current study's model, this rate was assumed to be based on laboratory-confirmed cases identified using standard nucleic acid amplification tests (such as RT–PCR) and/or validated antigen tests, consistent with surveillance definitions used during the COVID–19 pandemic. However, this value can be biased by testing access, changes in testing indications, and shifts from laboratory to home-based testing, and it can give an indication of trends over time (Couture et al. 2022). Because of this variability in testing practices and testing access, local public health surveillance data and facility-specific testing practices should be considered when selecting the positivity rate input for scenario analyses.

The hospitalization rate (Hosp_rate) is the percentage of cases that require hospitalization. This number varied widely throughout the COVID-19 pandemic, with temporal variation documented in multiple estimates: hospitalization rates were much higher during the peak of the pandemic (peak winter 2020–2021) and decreased as COVID-19 circulation and associated hospitalization rates stabilized at lower levels relative to peak waves. The term "endemic" was used cautiously to describe periods when COVID–19 circulation and associated hospitalization rates stabilized at lower levels relative to peak waves, rather than implying that all jurisdictions have fully transitioned to an endemic state or continue to report outcomes consistently (Townsend et al. 2023). Incomplete or discontinued morbidity and mortality reporting in some jurisdictions further complicates precise characterization of an endemic phase and contributes to uncertainty in hospitalization rate estimates used as model inputs This modeling framework is not specific to COVID-19 and can be applied to seasonal influenza or co-circulating respiratory pathogens, provided that pathogen-specific parameters (e.g., positivity rate, hospitalization rate, and vaccine effectiveness) are updated using current surveillance data. It was assumed that some fraction of cases that required hospitalization were admitted to another facility in the area, so the percentage of cases that "chose" this facility was noted as Percent_case_choose. NumHCW represented the total number of HCW in the facility, while NumPatHCW was the number of patient-facing HCW who had direct exposure to patients or infectious material. The hypothetical facility had 900 HCW, some portion of which were patient-facing, depending on the number of cases in the facility.

The variable PPE_Items is a list of PPE items that are appropriate for protecting HCW for a pandemic (COVID-19, in this example), including gloves, gowns, surgical masks, N95 respirators, and face shields. The standard precautions PPE ensemble (StdPr_PPE) and COVID-19 PPE ensemble (COVID_PPE) variables were indexed by PPE_Items. These variables represented the number of pieces of each PPE item that are used by one HCW each day based on standard precautions or if they are patient-facing, respectively. The PPE items included in this variable can be modified based on the recommended PPE for relevant exposures.

Model outputs

Intermediate outputs were calculated using the variables listed above. The percent of the catchment population with vaccine-induced immunity (Percent_VaxImmune) is the product of the percent of the population that is fully vaccinated and the effectiveness of full vaccination, plus the product of the percent of the population that is partially vaccinated and the effectiveness of partial vaccination.

$$\mathrm{Percent}_{\mathrm{VaxImmune}} = \left(Percent_{FullVax} * Full_{Vax_{Effec}}\right) + \left(Percent_{PartVax} * Part\_Vax\_Effec\right) \tag{10}$$

The number of susceptible people in the population (Suscept_Pop) was the number of individuals in the catchment area who were not considered to have vaccine-induced immunity and were therefore at risk of infection by the pathogen of interest. This aligned with standard epidemiological usage of “susceptible” in compartmental models, where a susceptible individual lacks sufficient immunity and can become infected (Lahariya 2016). In this simplified framework, susceptibility was defined only in terms of vaccination status and vaccine effectiveness; other sources of immunity (e.g., prior infection, hybrid immunity, or immunocompromise) could be incorporated in future versions of the model if data are available.

$$\mathrm{Suscept}_{\mathrm{Pop}} = Tot\_Pop - (Tot_{Pop} * Percent\_VaxImmune) \tag{11}$$

The total number of cases in the catchment area (Tot_cases) was the product of the number of susceptible people in the population and the positivity rate. The number of hospitalized cases (Hosp_cases) was the product of the total number of cases and the hospitalization rate (Hosp_rate). The number of cases at the facility (Facility_cases) was the percentage of hospitalized cases that chose or were sent to the facility instead of other facilities that were available to them.

$$Tot_{Cases} = Suscept_{Pop} * Pos\_Rate \tag{12}$$

$$Hosp_{Cases} = Tot_{cases} * Hosp\_rate \tag{13}$$

$$Facility_{cases} = Hosp_{cases} * Percent\_Case\_Choose \tag{14}$$

The simplifying assumption that the number of patient-facing HCWs was proportional to the number of COVID-19 cases in the hospital was made. Thus, the proportion of HCW that had contact with COVID-19 patients (NumPatHCW) was calculated by multiplying the total number of HCWs by a fraction of the number of cases in the facility.

$$\mathrm{NumPatHCW} = NumHCW * 0.001(facilitiy\_cases) \tag{15}$$

Using Equation 15, the number of patient-facing HCW exceeded the total number of HCW in the facility if the number of disease cases at the facility exceeded 1000. This allows the model to accommodate additional HCW workers (or existing HCW that work additional shifts) that may be added to the workforce during significant outbreaks.

The total amount of PPE needed was based on the total number of HCW and the number of HCW that will need additional PPE due to expected contact with patients or infectious materials. It was assumed that each HCW would need at least one set of standard precautions PPE. Patient-facing HCW required additional PPE due to their increased potential exposure. Thus, the total PPE needed was calculated as follows:

$$Total\ PPE\ Needed = \mathrm{StdPr}\_{\mathrm{PPE}} * \mathrm{NumHCW} + \mathrm{COVID}_{PPE} * \mathrm{NumPatHCW} \tag{16}$$

where $\mathrm{StdPr}\_{\mathrm{PPE}}$ = Standard precautions PPE items, NumHCW = total number of health care workers, $\mathrm{COVID}_{\mathrm{PPE}}$ = COVID-19 PPE items, and NumPatHCW = number of patient-facing HCWs (i.e., number of health care workers in contact with confirmed or suspected COVID-19 cases).

Predicting PPE needs in multiple scenarios

To demonstrate how the model can be used, the model was run under several conditions and forecasted PPE needs under specific circumstances. The inputs for each of the scenarios are listed in Table 2.

In the first hypothetical scenario, the percent of the population that was fully vaccinated (Percent_FullVax) was input as a normal distribution, with a mean of 0.5 and a standard deviation of 0.1, based on vaccination rates in major cities in the months following the release of the vaccine to adults of all ages and occupations (USAFacts.org 2021). While this example was based on country-wide trends and averages near the peak of the COVID-19 pandemic, users should modify inputs based on local conditions and scenario-specific data to improve model predictions. Other inputs included are also listed in Table 2. Scenario 1 was used as a base model, and inputs for Scenarios 2 and 3 were modified to understand how changes in certain variables would impact PPE needs.

In Scenario 2, the impact of increased vaccine uptake in the community was tested by modifying Percent_FullVax. The percentage of the population fully vaccinated was increased from 50% in Scenario 1 to 80% in Scenario 2. The percent of the population that was partially vaccinated remained 10%, and all other inputs were preserved from Scenario 1.

In Scenario 3, the effect of a more contagious and virulent variant of COVID-19 in which vaccines are less effective was simulated. Both the positivity rate and the hospitalization rate were modified from 10% to 20%, while decreasing the full and partial vaccine effectiveness as indicated in Table 2.

Table 2. Excel model inputs for each scenario.

Variable	Scenario 1: Base Model	Scenario 2: Increased local vaccination rates	Scenario 3: Emergence of more contagious and virulent variant
Percent of Population Fully Vaccinated (Percent_FullVax)	N (0.5, 0.1)	**TruncN (0.8, 0.1, 1.0)**	N (0.5, 0.1)
Percent of population partially vaccinated (Percent_PartVax)	TruncN (0.1, 0.03, 0)	**TruncN (0.1, 0.03, 0)**	N (0.1, 0.03)
Full Vaccine Effectiveness (Full_Vax_Effec)	TruncN (0.95, 0.05, 1.0)	TruncN (0.95, 0.05, 1.0)	**N (0.65, 0.05)**
Partial Vaccine Effectiveness (Part_Vax_Effec)	U (0.5, 0.8)	U (0.5, 0.8)	**U (0.2, 0.4)**
Total population (Tot_Pop)	N (100,000, 5,000)	N (100,000, 5,000)	N (100,000, 5,000)
Positivity Rate (Pos_Rate)	TruncN (0.1, 0.05, 0)	TruncN (0.1, 0.05, 0)	**TruncN (0.2, 0.05, 0)**
Hospitalization Rate (Hosp_rate)	TruncN (0.1, 0.01, 0)	TruncN (0.1, 0.01, 0)	**TruncN (0.2, 0.01, 0)**
Percent of cases choosing facility (percent_case_choose)	N (0.5, 0.05)	N (0.5, 0.05)	N (0.5, 0.05)
PPE Items (PPE_Items)	Gloves, Gown, Surgical Mask, N95 respirator, Face Shield	Gloves, Gown, Surgical Mask, N95 respirator, Face Shield	Gloves, Gown, Surgical Mask, N95 respirator, Face Shield
Standard Precautions PPE Ensemble (StdPr_PPE)	10,0,3,0,0 (indexed by PPE_Items)	10,0,3,0,0 (indexed by PPE_Items)	10,0,3,0,0 (indexed by PPE_Items)
COVID-19 PPE Ensemble (COVID_PPE)	10,3,3,10,3 (indexed by PPE_Items)	10,3,3,10,3 (indexed by PPE_Items)	10,3,3,10,3 (indexed by PPE_Items)
Number of health care workers (NumHCW)	U (900, 1,100)	U (900, 1,100)	U (900, 1,100)

Distributions and ranges used are reported as follows: N: Normal distribution with (mean, standard deviation). TruncN: Truncated normal distribution with (mean, standard deviation, point where distribution was truncated). U: Uniform distribution with (minimum, maximum). Standard precautions PPE and COVID-19 PPE ensembles are indexed by PPE Items, such that 10,0,3,0,0 represents 10 (pair) Gloves, 0 Gowns, 3 Surgical Masks, 0 N95 respirators, and 0 Face Shields. Scenario 1 is used as a base model. Values are bolded in Scenarios 2 through 4 where different from Scenario 1.

Table 3. PPE forecasting outputs in Excel model.

PPE Item	Scenario 1: Base Model	Scenario 2: Increased local vaccination rates	Scenario 3: Emergence of more contagious and virulent variant
Gloves	N (12,414, 1,471)	N (10,986, 970)	N (20,610, 3,588)
Gown	TruncN (724, 389, 0)	TruncN (296, 220, 0)	N (3,062, 1,032)
Surgical Masks	N (3,724, 441)	N (3296, 290)	N (6,061, 1,076)
N95 Respirator	TruncN (2,415, 1,296, 0)	TruncN (985, 734, 0)	N (10,207, 3,439)
Face Shield	TruncN (724, 389, 0)	TruncN (296, 220, 0)	N (3,062, 1,032)

Distributions and ranges used are reported as follows: N: Normal distribution with (mean, standard deviation). TruncN: Truncated normal distribution with (mean, standard deviation, point where distribution was truncated).

Results

Three hypothetical scenarios were modeled using the spreadsheet tool to predict PPE needs. Intermediate outputs of the model, such as the percentage of the population with vaccinated immunity, the number of cases in the catchment area that require hospitalization, and the number of HCWs with patient-facing interactions, are given in Supplementary Materials. Variation in intermediate outputs is a result of assumed variation in the inputs. Model outputs for forecasted PPE needs are given as a distribution of possible outcomes in Table 3.

For Scenario 1, the model predicted that 12,414 pairs of gloves (SD: 1,471); 724 gowns (SD:129); 3,724 surgical masks (SD: 441); 2,415 N95 Respirators (SD: 1,296), and 724 face shields (SD:389) were needed (Table 3). An increase of local vaccination rates (Scenario 2) from 50% and 10% fully and partially vaccinated to 80% and 10%, respectively, resulted in decreases in all PPE types. Gloves and surgical masks needed decreased by approximately 12%, while gowns, N95 respirators, and face shields needed to decrease by approximately 60% (Table 3). Based on the assumptions made regarding the emergence of a more contagious variant (Scenario 3), additional local cases of COVID-19 led to increased PPE needs in the model. The need for gloves and surgical masks increased by 66%, while other PPE items needed were predicted to increase by 322% (Table 3).

Additional scenarios that impact PPE requirements can also be modeled. Multiple variables can be modified at once to provide PPE forecasting appropriate for multiple specific facilities and to compare PPE needs as conditions change. For example, bed shortages in other facilities or in surrounding communities will result in an increase in the variable Percent_case_choose, and ultimately an increase in overall PPE needs at the facility (Table 4).

Discussion

The models presented in this paper are intentionally general to accommodate a wide variety of users.

Table 4. Possible modeling scenarios.

Scenario	Input variables modified	Overall impact on forecasted PPE needs
Local increases in vaccination rates	Percent_FullVax ↑ Percent_PartVax ↑	↓
Loss of vaccine effectiveness over time	Full_Vax_Effec↓ Part_Vax_Effec ↓	↑
Increased virulence/emergence of more virulent variants	Hosp_rate ↑	↑
Increased infectivity/emergence of more infectious variants	Pos_Rate ↑	↑
Bed shortages in other facilities or surrounding communities	Percent_case_choose↑	↑

Arrows indicate the direction that the variables will change under the given circumstances.

However, each model can be easily adapted to add scenario-specific considerations to improve utility. The CDC PPE Burn Rate Calculator was designed in an accessible Excel format so that users can modify the calculator to meet their specific needs. In general, the Burn Rate Calculator is modifiable to meet the needs of most users, and users can change the way that the burn rate is calculated (e.g., average burn rate over the entire period recorded versus a rolling average over a certain number of days/weeks). The calculated burn rates and recorded inventory records can signal if PPE shortages are likely and trigger the adoption of contingency and crisis capacity PPE strategies.

While the PPE Burn Rate Calculator and NIOSH PPE Tracker App are useful tools for recording past usage of PPE, there are limitations to their use. Most notably, these tools do not account for local changes in disease dynamics that greatly influence PPE needs. Relying on historical burn rate data alone will result in an underestimation of PPE needs if COVID-19 cases suddenly surge in the community. Therefore, models that can incorporate anticipated changes in disease trends are needed to make accurate predictions for future PPE needs. Together with the CDC Burn Rate Calculator of the NIOSH PPE Tracker App, the PPE forecasting model described in this paper provides a structure for the type of model that will be needed to make PPE supply chain decisions based on local COVID-19 conditions. The model can, and should, be modified freely based on consumption-related assumptions, including changes in local vaccination rates, additional information on vaccine uptake and effectiveness, and what is known about the newly emerging variants of the virus. Furthermore, the model can be used to predict the impact of changes in facility PPE practices.

Results presented for the forecasting model indicate that changes in local conditions can have significant impacts on facility-level PPE needs. These results show large increases in PPE needs based on changes in vaccination rates and the emergence of new variants of COVID-19. Relatively large standard deviations that correspond to a high degree of uncertainty in point estimates given by the model were recorded. This may reflect true possible variation in daily PPE needs, but also represents a large degree of uncertainty in the inputs, which is propagated through the model. True vaccination rates, community vaccine uptake, and other factors are often difficult to attain on a local level, and there will inevitably be large amounts of uncertainty around these inputs.

Given the recurring burden of seasonal influenza and the increasing likelihood of concurrent COVID-19 and influenza seasons, integrated forecasting of PPE for multiple respiratory viruses may help facilities and health systems anticipate combined surges in PPE needs. This modeling framework applies to seasonal influenza and other respiratory pathogens, provided that pathogen-specific parameters (vaccination rates, positivity rates, hospitalization rates, and vaccine effectiveness estimates) are updated using current surveillance data. Seasonal influenza remains a major source of morbidity and mortality, and PPE plays a critical role in protecting healthcare workers and vulnerable populations during seasonal epidemics.

PPE supply-chain disruptions and stockpile shortfalls were widely documented during the COVID-19 pandemic across multiple countries, including challenges with expiring inventory, quality variation, and competition for supplies. For example, Canada's Public Health Agency (PHAC) destroyed much of the national emergency stockpile before the pandemic, highlighting the importance of proactive stockpile management and regular inventory rotation. A substantial portion of global PPE manufacturing capacity is located in China and other countries that became critical exporters during the pandemic, leading to vulnerability when export restrictions, quality concerns, or transportation bottlenecks arose. These international experiences underscore that stockpile management and demand forecasting are concerns shared across jurisdictions rather than issues unique to the United States.

Simple, adaptable PPE forecasting tools of the type described here could support national and regional stockpile policies by:

- informing dynamic minimum stock levels based on projected local and regional surge scenarios (including influenza seasons);
- supporting rotation of stockpile inventory into routine use to reduce waste from expiration, with replenishment guided by model-based demand projections; and
- providing a quantitative basis for coordinating procurement across jurisdictions and internationally to avoid simultaneous surges in orders that strain global manufacturing capacity and international logistics networks.

Facility-level tools such as the one presented here can be integrated into broader regional or national planning frameworks—potentially across borders—to inform more coordinated procurement and stockpiling strategies that account for international manufacturing and logistics constraints. While a full comparative analysis of national policies is beyond the scope of this modeling paper, the tool is suitable for adaptation using country-specific data and has potential relevance to global PPE preparedness.

Limitations

As a base model for PPE prediction, there are many opportunities for enhancement of the model to accommodate the needs of a particular facility or situation. The current study's model does not currently address other situations that impact PPE needs, such as fit testing, the prevalence of other infectious diseases that require enhanced PPE, or the provision of PPE items, such as face masks, to the public. If relevant, the model should be modified to account for these factors.

Additionally, the current model does not specifically differentiate between the one-dose vaccine and the two-dose vaccines for COVID-19 approved for use in the United States. As defined in the current study's model, a person is considered "fully vaccinated" regardless of which vaccine they were administered or how long it has been since administration beyond two weeks. In this way, all three vaccines are considered equivalent in terms of effectiveness, despite reports that show vaccine effectiveness can vary significantly based on the specific vaccine administered and the time that has passed since vaccination. The model does not consider waning vaccine effectiveness over time, differences in vaccine efficacy based on the type of vaccine received or dosing schedule, or the impact of the booster shot on vaccine-induced immunity. These features can be incorporated in the model, but data for these parameters are difficult to attain, especially on a local level. While these factors are considered in light of the COVID-19 vaccines that were available at the peak of the pandemic, vaccine types and effectiveness may vary in future outbreaks or pandemics, as well.

The predominant variant in a community can have important impacts on the disease trends and the number of local COVID-19 cases. As seen in Scenario 3, inputs to the model, such as vaccine effectiveness, hospitalization rate, and positivity rate, may be modified to account for emerging COVID-19 variants (i.e., Delta and Omicron), but the model does not specifically track the impact of variants on case numbers and ultimately, PPE requirements. Unfortunately, current surveillance systems still struggle to capture these types of data accurately. The integration of sophisticated disease dynamics models will improve estimates of disease trends and consequently produce more accurate estimates of PPE needs. However, more sophisticated models require additional parameters that are often unknown or not easily attained.

Conclusions

The COVID-19 pandemic provided a clear example of how healthcare and other public facilities adopt new PPE elements to improve worker safety and the safety of the public. Both healthcare and non-healthcare facilities may experience challenges related to user proficiency, staff adherence to new work practice expectations, tracking PPE consumption, and obtaining consistent supplies of gloves, face shields or goggles, gowns, and isolation masks or N95 filtering facepiece respirators. Thus, facilities will need to anticipate and monitor their PPE usage so they can (1) place new orders before stock is depleted, (2) understand the impact of changing PPE use requirements, and (3) predict the impact of an increased number of patients requiring enhanced PPE practices. In emergency response scenarios, where practicality and usability are paramount, straightforward modeling tools designed with the end user in mind can have great utility for decision-making.

The COVID-19 pandemic exposed vulnerabilities in PPE supply chains on both a local and national level, highlighting the need for proactive, data-driven resource management strategies. Future events may suddenly and dramatically change the need for PPE or other supplies at healthcare facilities and other workplaces, similar to the initial emergency of the COVID-19 pandemic in early 2020. Mathematical models are an important strategy to aid in documenting PPE use and forecasting future PPE needs. The tool presented here goes beyond tracking PPE usage by providing a scalable, adaptable model that allows facilities to anticipate and respond to changing PPE needs in real time. The integration of scenario-specific variables and changes in local conditions can accommodate a variety of different scenarios requiring PPE.

Recommendation

As future pandemics and public health emergencies arise, mathematical models such as this one should be considered as an important approach to making data-informed decisions, ultimately reducing waste and better protecting workers. Predictive mathematical models offer the ability to move beyond reactive stockpiling toward strategic preparedness.

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Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary materials.

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