



# A Review of Mortality Risk Prediction Models in Smartphone Applications

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## Abstract

Healthcare professionals in healthcare systems need access to freely available, real-time, evidence-based mortality risk prediction smartphone applications to facilitate resource allocation. The objective of this study is to evaluate the quality of smartphone mobile health applications that include mortality prediction models, and corresponding information quality. We conducted a systematic review of commercially available smartphone applications in Google Play for Android, and iTunes for iOS smartphone applications. We performed initial screening, data extraction, and rated smartphone application quality using the Mobile Application Rating Scale: user version (uMARS). The information quality of smartphone applications was evaluated using two patient vignettes, representing low and high risk of mortality, based on critical care data from the Medical Information Mart for Intensive Care (MIMIC) III database. Out of 3051 evaluated smartphone applications, 33 met our final inclusion criteria. We identified 21 discrete mortality risk prediction models in smartphone applications. The most common mortality predicting models were Sequential Organ Failure Assessment (SOFA) ( $n = 15$ ) and Acute Physiology and Clinical Health Assessment II ( $n = 13$ ). The smartphone applications with the highest quality uMARS scores were *Observation—NEWS 2* (4.64) for iOS smartphones, and *MDCalc Medical Calculator* (4.75) for Android smartphones. All SOFA-based smartphone applications provided consistent information quality with the original SOFA model for both the low and high-risk patient vignettes. We identified freely available, high-quality mortality risk prediction smartphone applications that can be used by healthcare professionals to make evidence-based decisions in critical care environments.

**Keywords** Severity of illness index · Hospital mortality · Mobile applications · Intensive care units

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## Introduction

Critical care is a complex and multidisciplinary specialty designed to care for patients with critical illnesses [1]. In intensive care units (ICU), healthcare professionals use mortality prediction models (MPMs) to triage patients [2–4], quantify the risk of sepsis and death [5, 6], and to estimate the cost of medical treatment [7–9]. MPMs are also used to prognosticate weaning from ventilators, length of ICU stay, mortality, and rate of recovery [10–15]. The MPM algorithms use physiologic measures [16] within 24 h of admission into the ICU [17] to calculate a risk score [18, 19]. In combination with other patient-level variables, MPMs help healthcare professionals identify patients who will likely need additional intensive care support [20, 21]. The three most common MPMs are: Acute Physiology and Clinical Health

Assessment (APACHE), Sequential Organ Failure Assessment (SOFA), and Simplified Acute Physiology Assessment (SAPS) [5, 6]. The choice of MPM depends on the ease of use, effectiveness and reliability in the critical care environment [17].

Advances in point of care technologies, including smartphones [22] have played a key role in advancing access to healthcare information at the bedside [13], with critical care medicine at the forefront of these advances [23]. Healthcare professionals have been increasingly using smartphone applications (apps) in practice to provide users easier and faster real-time access to different models, to enhance decision making [24, 25], and assist in patient monitoring, counseling, data collection, and documentation [26]. In many countries that do not have access to electronic medical records (EMR) that automatically calculate MPM scores, healthcare professionals are using their smartphones to calculate these risk scores using apps [27–29].

The rapid global spread of COVID-19 has made smartphone-based MPM models increasingly relevant, especially as hospitals around the world converted operating rooms and medical units to intensive care units to handle patient volume [30–32]. Using stand-alone apps for risk prediction can support healthcare professionals who are providing inpatient care for patients [30–34], especially in the ICUs. Given the shortage of resources and increased risk of sepsis and death, the use of MPMs by healthcare professionals can facilitate clinical decision making [5, 6]. In this systematic review of commercially available apps, we evaluated both overall quality and information quality of MPMs.

## Methods

### Stage 1: Selection of the search strategy

The *Population Intervention Comparison Output* (PICO) [35] framework was used to develop the research question. *Population* was ICU professionals, the *intervention* was MPMs in apps for critically ill patients in ICUs, and the *output* was information quality of MPMs in apps—there was no *comparison* in this study. Reporting for this systematic review followed Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) recommendations [36]. We used the following search terms: "ICU mortality", "mortality scoring system", "APACHE", "SOFA", "SAPS", "NEWS", "MODS", "LODS" and "medical calculator" for identifying MPMs in apps. Inclusion

criteria included being freely available and in English. Apps were excluded if they could not be identified by the name, icon, or description, and require in-app purchases for the MPM.

### Stage 2: Screening and selection of the apps

We conducted the first screening of apps in January 2020, and the secondary screening of apps in June 2020. Each keyword was used separately in Google Play and iTunes. We used iPadium [37] as a simulator for apps in the iTunes stores to be able to conduct the evaluations on a desktop computer. Duplicate apps from each search term in the smartphone app store and simulator were removed after they were copied into Excel spreadsheets independently by two authors (NF, LG). A third author was available for a discussion to help resolve disagreements in scores (GS). Apps which met inclusion criteria were downloaded and evaluated on a Samsung Galaxy S8 phone (Android 9.0) and iPhone 7 (iOS 12.3.1). The apps were sorted into two groups based on whether they included single or multiple MPM medical calculators.

### Stage 3: Evaluation of the quality of the overall apps

The quality of apps was evaluated with the Mobile Application Rating Scale: user version (uMARS) [38] by two ICU nurses with over five years of critical care experience. The uMARS contains four objective quality scales: engagement, functionality, aesthetics, information quality, and one subjective quality assessment, all of which are graded on a five-point scale. The subjective quality and perceived impact of uMARS was not calculated. Interrater reliability was computed using R version 3.6.0 [39].

### Stage 4: Evaluation of apps provided information quality

We used the freely available Medical Information Mart for Intensive Care III (MIMIC III), version 1.3 [40], which contains over 10 years (2001–2012) of de-identified critical care data from 46,520 ICU patients at Beth Israel Deaconess in Boston. Using the MIMIC III database, we developed two patient vignettes representing low and high risk of mortality based on SOFA scores. The SOFA MPM has six different scores, ranging from 0 to 4 for each organ system (respiratory, cardiovascular, hepatic, coagulation, renal, and neurological) [41]. The low-risk patient vignette had a SOFA score for each organ system from 0 to 2, and the high-risk vignette who had a SOFA score of 2 to 4 for

each organ system. The data were analysed using R, version 3.6.0 [39].

## Results

As reported in our PRISMA flow diagram, we identified 3051 apps. After removing duplicates between keywords, 2758 apps remained. Based on pre-specified exclusion criteria (e.g., inappropriate name, icon, imagery, and images), we excluded 2690 apps. We added 5 apps after secondary app screening. After downloading and testing apps, a total of 33 apps were included in the final analysis (Fig. 1 and Table 1). Inter-rater reliability between raters for the uMARS was acceptable (reviewer one vs. reviewer two;  $K_{\text{alpha}} = 0.89$ ).

The quality of apps was evaluated using a standardized methodology, including the uMARS tool, and the overall uMARS app quality score was 3.66 (SD = 0.65), which is considered as a moderate overall quality in comparison to the other studies [42–46]. Overall, 33.3% ( $n = 11$ ) of the apps were developed by small or medium-sized enterprises, 6.1% ( $n = 2$ ) by healthcare-related agencies, and 3% ( $n = 1$ ) by an educational organization (Table 1). Apps developed by individuals had lower overall quality, compared to apps developed by enterprises, educational or healthcare institutions ( $M = 3.40$ ;  $SD = 0.52$  vs.  $M = 3.88$ ;  $SD = 0.68$ ;  $p = 0.001$ ). The top-rated app was *MDCalc Medical Calculator* (4.75), which also had high ratings across all four domains.

We identified 21 different MPMs in apps. The most common MPMs in apps were SOFA ( $n = 15$ ) and APACHE II ( $n = 13$ ) (Fig. 2).

Less than a half of the apps ( $n = 13$ ) included multiple MPM calculators (e.g., *Nursing calculator* with SOFA and MEWS) and the others ( $n = 20$ ), included a single MPM calculator. Two apps, *MDCalc Medical Calculator* and *Doctor Calci* included a total of 10 different MPMs (Table 2). Single MPM medical calculators had a lower mean app quality score ( $M = 3.37$ ;  $SD = 0.57$ ;  $p = 0.002$ ) compared to multiple MPM medical calculators ( $M = 4.03$ ;  $SD = 0.52$ ).

Table 3 represents a list of 23 clinical variables in SOFA-based apps ( $n = 15$ ). Variables were divided into six organ systems, as described by Vincent and colleagues in the SOFA validation study [41]. The lowest number of included variables in apps was 6 (e.g., app 3: *SOFA*), and the highest was 15 (e.g., app 24: *Medical Calculators*). Clinical data were most commonly inserted into the SOFA-based app using either a drop-down menu, or they were selected from a pre-populated list.

We evaluated the information quality of each of the SOFA-based apps against the low and high-risk vignettes, where low-risk vignette had a count of 6 points on the SOFA score and the high-risk vignette had a count of 18 points on the SOFA score (Table 4). There was greater variation (from < 10% to < 33%) in the risk of mortality in the lower risk vignette (Table 5).

## Discussion

Healthcare professionals need accurate, real-time, high quality information to make medical decisions for the most vulnerable patients in critical care environments. Many hospitals worldwide do not have EMRs, which calculate mortality risk prediction; therefore, smartphone-based MPMs are commonly used in clinical practice to predict hospital mortality [27–29]. This study systematically reviewed both the overall app quality and information quality of MPMs in apps.

Based on the overall uMARS quality assessment, the MPM apps provided moderate information quality. The most commonly downloaded app, *MDCalc medical calculator*, also had the highest quality rating and the most comprehensive, evidence-based MPM information. The highest rated apps had better visual information and incorporated high-quality scientific evidence [67, 68]. Most apps for mortality prediction are designed to optimize speed and minimize manual data entry (e.g., numeric text input) by using drop-down menus or choosing from a pre-populated list. The limitation of pre-populated values is that they may not include some value ranges, or they may not enable the functionality to toggle between metric and imperial units [69]. For example, *MDCalc Medical Calculator* resolved this problem by including a choice between units and providing additional alerts for healthcare professionals to check the input values. Relevant to protecting patient privacy, none of the apps included personally identifiable information.

To evaluate information quality, we used the SOFA score, because, in this review, it was the most widely used MPM across all of the apps. The apps generate a SOFA score and percentage for ICU mortality risk, which healthcare professionals interpret and use for medical decision making. When the quality of the MPM apps was evaluated against the two vignettes, the consistency of the app generated a high risk of mortality for the sicker patient and consistent scores for the lower risk patient, but with variability in the risk of mortality. We speculated that the discrepancies were due to differences in mortality algorithms and

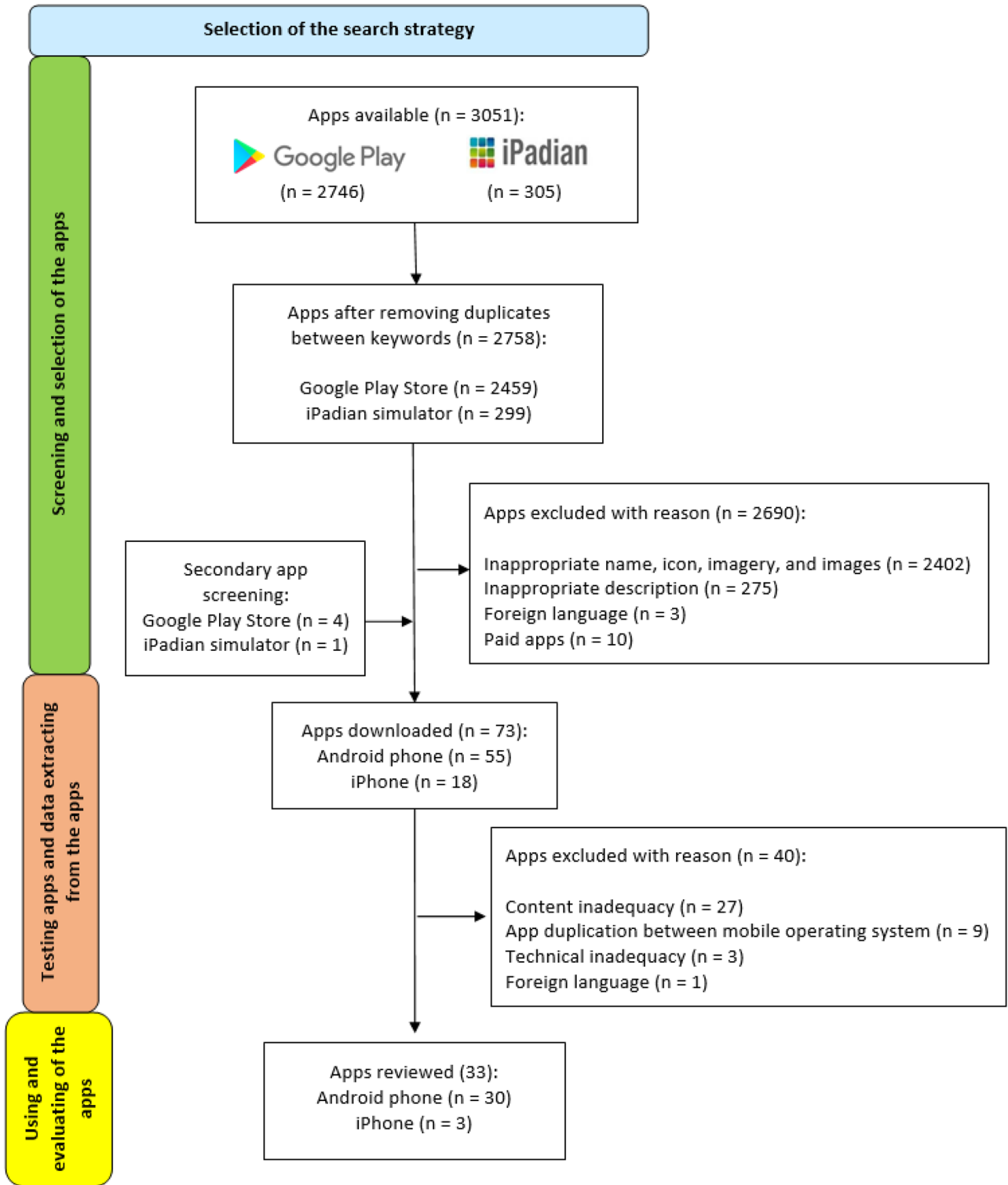


Fig. 1 PRISMA flow diagram

**Table 1** Descriptive characteristics of included apps and uMARS app quality scores

Descriptive characteristics				uMARS sections
Name of apps	Short name	MOS	App origin	Engagement (mean score)
1. SOFA—Sepsis-related Organ Failure Assessment	App 1	AND	Individuals	2.80
2. Apache II Score	App 2	AND	Individuals	3.30
3. SOFA	App 3	AND	Individuals	3.40
4. SOFA Score	App 4	AND	Individuals	3.40
5. SAPS 3 Calc	App 5	AND	Individuals	3.50
6. Sepsis Score: SOFA Calculator	App 6	AND	Individuals	3.40
7. qSOFA Score calculator	App 7	AND	Individuals	3.20
8. qSOFA Score Calculator	App 8	AND	Individuals	3.20
9. SOFA score	App 9	AND	Individuals	3.30
10. MEWS (Modified Early Warning Score)	App 10	AND	Individuals	2.60
11. NEWS2 Chart	App 11	AND	Individuals	2.80
12. NEWS score	App 12	AND	Individuals	2.70
13. NEWS 2—National Early Warning Score 2017	App 13	AND	Individuals	2.70
14. Observation—NEWS 2	App 14	iOS	Small and Medium-sized Enterprises	3.70
15. RRAPID	App 15	iOS	Educational Organizations	2.50
16. MEWS	App 16	iOS	Individuals	2.90
17. NEWS Wales	App 17	AND	Healthcare related Agency	2.80 2.80
18. Medical Formulas	App 18	AND	Individuals	3.60
19. EP Mobile	App 19	AND	Small and Medium-sized Enterprises	3.50
20. MedCal Lite Fastest Medical Calculator	App 20	AND	Individuals	3.90
21. Nursing Calculator	App 21	AND	Individuals	2.90
22. Nursing	App 22	AND	Individuals	3.40
23. Doctor Calci	App 23	AND	Small and Medium-sized Enterprises	3.60
24. Medical Calculators	App 24	AND	Individuals	<b>4.30</b>
25. NEWS & SEPSIS SCREENING	App 25	AND	Healthcare related Agency	3.50
26. Calculate by QxMD	App 26	AND	Small and Medium-sized Enterprises	3.60
27. Coly ICU	App 27	AND	Small and Medium-sized Enterprises	3.30
28. 3C Critical Care Calculators	App 28	AND	Small and Medium-sized Enterprises	3.40
29. MDCalc Medical Calculator	App 29	AND	Small and Medium-sized Enterprises	4.30
30. MediCalc®	App 30	AND	Small and Medium-sized Enterprises	4.10
31. SEPSIS 3	App 31	AND	Small and Medium-sized Enterprises	3.90
32. Sepsis Clinical Guide	App 32	AND	Small and Medium-sized Enterprises	3.90
33. NCalc	App 33	AND	Small and Medium-sized Enterprises	2.90
MOS = mobile operating system; AND = Android				
<b>Total mean (SD)</b>				3.35 (0.48)

## Descriptive characteristics

Name of apps	Functionality (mean score)	Aesthetics (mean score)	Information (mean score)	App quality (mean score)
1. SOFA—Sepsis-related Organ Failure Assessment	3.88	2.67	2.17	2.88
2. Apache II Score	3.5	3.33	2.5	3.16
3. SOFA	4.38	4.17	3	3.74
4. SOFA Score	4.38	4.17	3.83	3.95
5. SAPS 3 Calc	3.5	3.33	4	3.58
6. Sepsis Score: SOFA Calculator	4.75	3.67	3.38	3.8

**Table 1** (continued)

Descriptive characteristics				
Name of apps	Functionality (mean score)	Aesthetics (mean score)	Information (mean score)	App quality (mean score)
7. qSOFA Score calculator	4.88	3.5	3.13	3.68
8. qSOFA Score Calculator	4.5	2.5	2.5	3.18
9. SOFA score	4.88	3.5	2.5	3.54
10. MEWS (Modified Early Warning Score)	3.88	2.33	2.33	2.79
11. NEWS2 Chart	3.13	2.33	2.33	2.65
12. NEWS score	3.5	2.33	2.33	2.72
13. NEWS 2—National Early Warning Score 2017	3.5	2.33	2.33	2.72
14. Observation—NEWS 2	<b>5</b>	<b>5</b>	4.88	4.64
15. RRAPID	4.13	2	2.13	2.69
16. MEWS	4.75	3.5	1.75	3.23
17. NEWS Wales	3.13 3.13	2.83 2.5	2.58 2.25	2.84 2.67
18. Medical Formulas	3.88	3.83	4.5	3.95
19. EP Mobile	3.5	3.33	4	3.58
20. MedCal Lite Fastest Medical Calculator	4.13	3.83	4.5	4.09
21. Nursing Calculator	3.88	3.17	3	3.24
22. Nursing	3.38	3.33	3.33	3.36
23. Doctor Calci	4.75	4.33	4.5	4.3
24. Medical Calculators	4.63	4.33	4.33	4.4
25. NEWS & SEPSIS SCREENING	3.88	4	4.17	3.89
26. Calculate by QxMD	4.75	3.67	3.83	3.96
27. Coly ICU	4.75	4	4.33	4.1
28. 3C Critical Care Calculators	4.88	3.83	3.17	3.82
29. MDCalc Medical Calculator	4.88	4.83	<b>5</b>	<b>4.75</b>
30. MediCalc®	5	4.33	<b>5</b>	4.61
31. SEPSIS 3	5	4.33	<b>5</b>	4.56
32. Sepsis Clinical Guide	4.38	4.33	4.33	4.24
33. NCalc	4.13	3.17	2.5	3.17
MOS = mobile operating system; AND = Android	4.25–0.62	3.53–0.77	3.51–1.07	3.66–0.65

potential differences in predictions for in-hospital versus 30-day mortality.

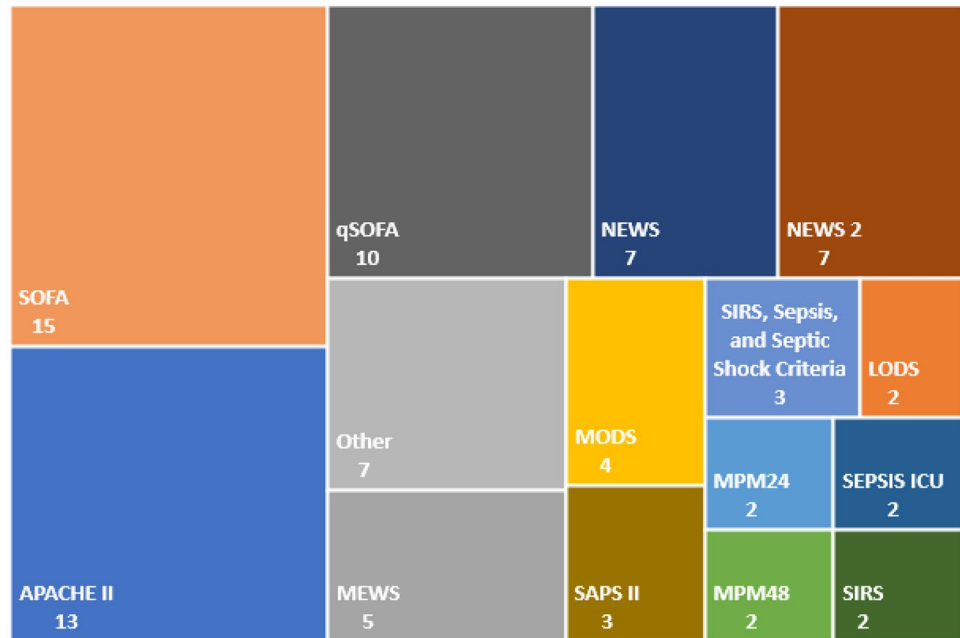
In addition, there was a wide variety of clinical variables that were used as predictors of mortality in SOFA-based apps, which was particularly relevant to the respiratory and cardiovascular organ systems. For example, when classifying respiratory function,  $\text{PaO}_2/\text{FiO}_2$  can be classified individually as the Carrico index or separately. From the perspective of the healthcare professional end user, this can be confusing and a barrier to clinical utility [70].

Smartphone app stores, like Google Play Store and App Store, should consider adding additional review criteria to include a rating for the scientific information quality of apps. The United Kingdom National Health Service [71] uses a

publicly available app review service, Organization for the Review of Care and Health Applications [72], where users can find a list of healthcare apps that have been evaluated by healthcare professionals.

Future research should focus specifically on which apps are most applicable for patients with COVID-19. Paradoxically, among patients with COVID-19 in-hospital deaths are associated with low SOFA scores [17, 73, 74]. As such, MPM apps should include relevant laboratory values such as D-dimer and neutrophil to lymphocyte ratio [75–80], to better predict ICU mortality risk for patients with COVID-19. These findings are consistent with recent COVID-19 clinical trials, which also used SOFA and APACHE II most frequently [17, 74, 75, 81–83]. Some pandemic triage plans and protocols [84–86]

**Fig. 2** Distribution of mortality prediction model in evaluated apps. The “Other” category includes MPMs that were included only once (i.e., APACHE III, APACHE IV, ICD mortality risk score, mSOFA, REMS, SAPS III, SIRS, and Sepsis Assessment)



recommend the use of SOFA MPMs for diagnosis and management of COVID-19, while others do not [87].

A few important limitations are recognized in the study. Firstly, our two calculated vignettes based on the MIMIC III database may not represent patients who may or may not be at high or low-risk of mortality. For example, the high-risk patient vignette had a SOFA score of 18 but was not on mechanical ventilation, which most of the higher risk of ICU mortality patients are on. On

the other hand, the mean SOFA calculated for lower-risk patient vignettes was similar to hospitalized COVID-19 patients [17, 74, 75, 81–83], who do have a high risk of mortality. A better solution for developing vignettes to evaluate the quality of the information provided by apps can be found in published papers where vignettes are based on the mean values of clinical parameters. A second limitation is that there are regional adaptations in the smartphone app stores, and, in this case, the search

**Table 2** Single and multiple mortality prediction model calculators

MPMs in apps	Single mortality prediction model calculators																
	App 1	App 2	App 3	App 4	App 5	App 6	App 7	App 8	App 9	App 10	App 11	App 12	App 13	App 14	App 15	App 16	App 17
1. SOFA	X		X	X		X			X								
2. qSOFA							X	X									
3. mSOFA																	
4. APACHE II		X															
5. APACHE III																	
6. APACHE IV																	
7. NEWS												X			X		X
8. NEWS 2											X		X	X			
9. MEWS										X							X
10. MODS																	
11. SAPS II																	
12. SAPS III					X												
13. SSSSC																	
14. SIRS																	
15. SEPSIS-3																	
16. SIRS&SA																	
17. LODS																	

**Table 2** (Continued)

MPMs in apps	Single mortality prediction model calculators																
	App 1	App 2	App 3	App 4	App 5	App 6	App 7	App 8	App 9	App 10	App 11	App 12	App 13	App 14	App 15	App 16	App 17
18. MPM <sub>24</sub>																	
19. MPM <sub>48</sub>																	
20. REMS																	
21. ICD MRS																	
<b>Sum MPM:</b>	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MPMs in apps	Single mortality prediction model calculators			Multiple mortality prediction model calculators													
	App 18	App 19	App 20	App 21	App 22	App 23	App 24	App 25	App 26	App 27	App 28	App 29	App 30	App 31	App 32	App 33	
1. SOFA				X	X	X	X		X		X	X	X	X	X		
2. qSOFA						X		X	X		X	X	X	X	X		
3. mSOFA												X					
4. APACHE II	X		X		X	X	X		X	X	X	X	X	X	X		
5. APACHE III						X											
6. APACHE IV						X											
7. NEWS								X				X	X			X	
8. NEWS 2												X	X		X	X	
9. MEWS				X					X			X					
10. MODS						X				X	X				X		
11. SAPS II						X						X			X		
12. SAPS III												X					
13. SSSSC						X					X	X					
14. SIRS													X	X			
15. SEPSIS-3													X	X			
16. SIRS&SA															X		
17. LODS													X	X			
18. MPM <sub>24</sub>						X				X							
19. MPM <sub>48</sub>						X				X							
20. REMS												X					
21. ICD MRS		X															
<b>Sum MPM:</b>	1	1	1	2	2	10	2	2	4	4	5	10	8	6	7	2	

MPMs: Sequential Organ Failure Assessment (SOFA [11, 41, 47]), Quick SOFA (qSOFA) [48]), Modified SOFA (mSOFA [3]), Acute Physiology and Clinical Health Assessment (APACHE II-IV [49–52]), National Early Warning Score (NEW [53], NEWS2 [54], MEWS [55]), Multiple Organ Dysfunction Syndrome (MODS [56]), Simplified Acute Physiology Assessment (SAPS II-III [57–59]), Systemic Inflammatory Response Syndrome, Sepsis, and Septic Shock Criteria (SSSSC [60]), Systemic Inflammatory Response Syndrome (SIRS [61]), Third International Consensus Definitions for Sepsis and Septic Shock (SEPSIS-3 [62]), SIRS and Sepsis Assessment (SIRS&SA [60]), Logistic Organ Dysfunction System (LODS [63]), Mortality Probability Model (MPM<sub>24, 48</sub> [64]), Rapid Emergency Medicine Score (REMS [65]), and ICD mortality risk score (ICD MRS [66])

was conducted using a European IP address so that it may have influenced the final set of apps obtained from the search engine. A potential bias of the review was the inclusion of freely available apps; however, this was a deliberate decision to represent available apps that do not pose a financial burden on the end-user, and are accessible to a wide audience of healthcare professionals, inclusive of low- and middle-income countries.

An important application of this work is for the education of healthcare professionals. Combining themes with vignettes based on simulation learning can increase student knowledge, critical thinking, and psychomotor skills for performing a better clinical evaluation of future patients [25]. For the next reviews, researchers should include specific medical calculator’s apps because they provide relevant information.



**Table 3** Clinical variables included in SOFA-based apps

Organ systems	Critical variables	SOFA-based apps ( <i>n</i> = 15)																
		App 1	App 3	App 4	App 6	App 9	App 21	App 22	App 23	App 24	App 26	App 28	App 29	App 30	App 31	App 32		
<b>Respiration</b>	PaO <sub>2</sub> /FiO <sub>2</sub>	S					D											
	PaO <sub>2</sub> /FiO <sub>2</sub> and respiratory support		D	D	D	D	D	D									D	
	PaO <sub>2</sub>				N	N			N	N	N	N	N	N	N	N	N	
	FiO <sub>2</sub>				N	N			N	N	N	N	N	N	N	N	N	
<b>Coagulation</b>	Respiratory support				D	D												
	Platelets	S	D	D	N	D	D	D	N	D	D	D	D	N	N	N	D	
	Bilirubin	S	D	D	N	D	D	D	N	D	D	D	D	N	N	N	D	
	<b>Liver</b>	Systolic blood pressure				N	N			N	N				N	N	N	
Diastolic blood pressure					N	N			N	N				N	N	N		
Mean arterial pressure		S			N	N	D	D		D							D	
Mean arterial pressure OR administration of vasoactive agents required			D	D	D	D	D	D		D							D	
<b>Cardiovascular</b>	Norepinephrine or Epinephrine or Dopamine or Dobutamine	S																
	Norepinephrine or Epi-nephrine																	
	Dopamine																	
	Dobutamine																	
	Epinephrine																	
	Norepinephrine																	
	Glasgow Coma Score	S	D	D	N	D	D	D	D	D	D	D	D	D	D	D	D	
	Eye response																	
	Verbal response																	
	Motor response																	
	Creatinine or urine output	S	D	D	N	D	D	D	D	N	D	D	D	N	N	N	D	
<b>Renal</b>	Creatinine																	
	Urine output																	
<b>Number of variables in app:</b>		7	6	6	6	6	6	6	8	8	6	6	6	6	8	13	13	6

N: numeric text input; D: drop-down menu or pre-populate list; S: slider with selection intervals

**Table 4** Mean clinical values and SOFA scores for low and high-risk patient vignette

Critical variables	Mean values for low-risk patient vignette*	SOFA points for low-risk vignette**	Mean values for high-risk patient vignette*	SOFA points for high-risk vignette**
<b>PaO<sub>2</sub>/FiO<sub>2</sub> ratio</b>	<b>308.2</b>	<b>+ 1</b>	<b>229.3</b>	<b>+ 2</b>
PaO <sub>2</sub> mmHg	151		133	
FiO <sub>2</sub> %	49		58	
Mechanical ventilation	No		No	
<b>Platelets, 10<sup>9</sup>/L</b>	<b>118.1</b>	<b>+ 1</b>	<b>40.4</b>	<b>+ 3</b>
<b>Bilirubin, g/L</b>	<b>1.8</b>	<b>+ 1</b>	<b>20</b>	<b>+ 4</b>
<b>Mean arterial pressure, mm Hg</b>	<b>73</b>	<b>0</b>	<b>53</b>	<b>+ 3</b>
Systolic blood pressure, mm Hg	110		82	
Diastolic blood pressure, mm Hg	55		38	
Vasopressors	No		Dopamine > 5 or Epinephrine > 0.1 or Norepinephrine > 0.1	
<b>Glasgow coma scale</b>	<b>12</b>	<b>+ 2</b>	<b>8</b>	<b>+ 3</b>
Best eye response	3		3	
Best verbal response	4		2	
Best motor response	5		3	
<b>Creatinine</b>	<b>1.3</b>	<b>+ 1</b>	<b>3.8</b>	<b>+ 3</b>
Urine output, mL/day	2900		250	
<b>Total SOFA points</b>		<b>6 points</b>		<b>18 points</b>

\* Average number was calculated using MIMIC III database; \*\* SOFA points were calculated using original SOFA publication [41]

**Table 5** SOFA score and percent of mortality in SOFA-based apps

	Short name	Low mortality risk patient vignette		High mortality risk patient vignette	
		SOFA score	% of mortality	SOFA score	% of mortality
SOFA-based apps ( <i>n</i> = 15)	App 1	6	N/A	18	N/A
	App 3	6	< 10%	18	> 90%
	App 4	6	< 10%	18	> 90%
	App 6	6	< 10%	18	> 90%
	App 9	6	N/A	18	N/A
	App 21	6	N/A	18	N/A
	App 22	6	N/A	18	N/A
	App 23	6	< 10%	18	> 90%
	App 24	6	N/A	18	N/A
	App 26	6	N/A	18	N/A
	App 28	6	< 10%	18	> 90%
	App 29	6	< 33%	18	> 95%
	App 30	6	< 33%	18	95%
	App 31	6	< 33%	18	95%
App 32	6	22%	18	95%	

N/A: The score was calculated but not the % of mortality

## Conclusion

There is pressing urgency in ICU environments globally for accurate mortality risk prediction. Results from this systematic review support the overall quality and information quality of the *MDCalc Medical Calculator*

for in-hospital mortality risk prediction. The benefits of *MDCalc Medical Calculator* are that it was developed to be used by healthcare professionals for critically ill adult ICU patients, it is available on both Android and iOS platforms, free, uses validated mortality prediction models, includes high-quality information MPMs, has less

time-consuming methods for data entry, includes metric and imperial units, and is regularly updated. The *MDCalc* and *Calculate by QxMD* webpages also provide separate COVID-19 smartphone-based MPM calculators, which can be used when atypical physical spaces in healthcare systems are being used as make-shift ICUs. Smartphone MPMs can also be used for non-ICU patients to estimate time to potential clinical deterioration [88], or for triaging an ICU patient for palliative care services [86, 89].

**Authors' contributions** The evaluation presented here was carried out in collaboration with all authors. NF developed a study design and supervised the study. NF, LC, and RMC drafted the manuscript. NF, LG, GS, and PK conducted data collection and analysis. PC interpreted results from a medical point of view. RMC conducted a comprehensive content review. All authors read, revised, and approved the final manuscript.

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## Declarations

**Conflicts Of interest/Competing interests** None declared.

## References

- Vincent JL (2013) Critical care – where have we been and where are we going? *Critical care* 17(Suppl 1):1–6. <https://doi.org/10.1186/cc11500>
- Jain A, Palta S, Saroa R, Palta A, Sama S, Gombar S (2016) Sequential organ failure assessment scoring and prediction of patient's outcome in Intensive Care Unit of a tertiary care hospital. *J Anaesthesiol Clin Pharmacol* 32(3):364–368. <https://doi.org/10.4103/0970-9185.168165>
- Grissom CK, Brown SM, Kuttler KG, Boltax JP, Jones J, Jephson AR, Orme JF (2010) A modified sequential organ failure assessment score for critical care triage. *Disaster Med Public Health Prep* 4:277–284. <https://doi.org/10.1001/dmp.2010.404>
- Rapsang AG, Shyam DC (2014) Scoring systems in the intensive care unit: A compendium. *Indian J Crit Care Med* 18:220–228. <https://doi.org/10.4103/0972-5229.130573>
- Johnson S, Saranya A (2015) Comparison of Different Scoring Systems Used in the Intensive Care Unit. *J Pulm Respir Med* 5:2. <https://doi.org/10.4172/2161-105X.1000276>
- Penoyer DA (2010) Nurse staffing and patient outcomes in critical care: A concise review. *Crit Care Med* 38:1521–1528. <https://doi.org/10.1097/CCM.0b013e3181e47888>
- Afshar M, Arain E, Ye C, Gilbert E, Xie M, Lee J, Churpek MM, Durazo-Arvizu R, Markossian T, Joyce C (2019) Patient Outcomes and Cost-Effectiveness of a Sepsis Care Quality Improvement Program in a Health System. *Crit Care Med* 47:1371–1379. <https://doi.org/10.1097/CCM.0000000000003919>
- Edbrooke DL, Minelli C, Mills GH, Iapichino G, Pezzi A, Corbella D, Jacobs P, Lippert A, Wiis J, Pesenti A, Patroniti N (2011) Implications of ICU triage decisions on patient mortality: A cost-effectiveness analysis. *Crit Care* 15:1–9. <https://doi.org/10.1186/cc10029>
- Glance LG, Osler T, Shinozaki T (1998) Intensive care unit prognostic scoring systems to predict death: a cost-effectiveness analysis. *Crit Care Med* 26:1842–1849. <https://doi.org/10.1097/00003246-199811000-00026>
- Dehghani A, Abdeyazdan G, Davaridolatabadi E (2016) An Overview of the Predictor Standard Tools for Patient Weaning from Mechanical Ventilation. *Electronic physician* 8:1955–1963. <https://doi.org/10.19082/1955>
- Lambden S, Laterre PF, Levy MM, Francois B (2019) The SOFA score - Development, utility and challenges of accurate assessment in clinical trials. *Crit Care* 23:1–9. <https://doi.org/10.1186/s13054-019-2663-7>
- Jain A, Palta S, Saroa R, Palta A, Sama S, Gombar S (2016) Sequential organ failure assessment scoring and prediction of patient's outcome in Intensive Care Unit of a tertiary care hospital. *J Anaesthesiol Clin Pharmacol* 32:364. <https://doi.org/10.4103/0970-9185.168165>
- Jones AE, Trzeciak S, Kline JA (2009) The Sequential Organ Failure Assessment score for predicting outcome in patients with severe sepsis and evidence of hypoperfusion at the time of emergency department presentation. *Crit Care Med* 37:1649–1654. <https://doi.org/10.1097/CCM.0b013e31819def97>
- Goodwin AJ (2019) Can Serial qSOFA Measurement Aid in Sepsis Identification and Triage Decisions?. *Critical care medicine* 46:2046–2048. <https://doi.org/10.1097/CCM.0000000000003417>
- Kim Y, Kim K, Jang I (2019) Analysis of mortality prognostic factors using model for end-stage liver disease with incorporation of serum-sodium classification for liver cirrhosis complications: A retrospective cohort study. *Medicine (Baltimore)* 98(45):e17862. <https://doi.org/10.1097/MD.00000000000017862>
- Sekulic AD, Trpkovic S V., Pavlovic AP, Marinkovic OM, Ilic AN (2015) Scoring Systems in Assessing Survival of Critically Ill ICU Patients. *Med Sci Monit* 21:2621–2629. <https://doi.org/10.12659/MSM.894153>
- Yang X, Yu Y, Xu J, Shu H, Xia J, Liu H, Wu Y, Zhang L, Yu Z, Fang M, Yu T, Wang Y (2020) Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study. *Lancet Respir Med*. Elsevier Ltd 8:475–481. [https://doi.org/10.1016/S2213-2600\(20\)30079-5](https://doi.org/10.1016/S2213-2600(20)30079-5)
- Collins SA, Cato K, Albers D, Scott K, Stetson PD, Bakken S, Vawdrey DK (2013) Relationship between nursing documentation and patients' mortality. *American Journal of Critical Care* 22:306–13. <https://doi.org/10.4037/ajcc2013426>
- Goldstein BA, Navar AM, Pencina MJ, Ioannidis JPA (2016) Opportunities and challenges in developing risk prediction models with electronic health records data: a systematic review. *Journal of the American Medical Informatics Association* 24:198–208. <https://doi.org/10.1093/jamia/ocw042>
- Moons KGM, Royston P, Vergouwe Y, Grobbee DE, Altman DG (2009) Prognosis and prognostic research: what, why, and how? *BMJ* 338:B375. <https://doi.org/10.1136/bmj.b375>
- Wyatt JC, Altman DG (1995) Commentary: Prognostic models: clinically useful or quickly forgotten? *BMJ* 311:1539–1541. <https://doi.org/10.1136/bmj.311.7019.1539>
- Hollander JE, Carr BG (2020) Virtually Perfect? Telemedicine for Covid-19. *N Engl J Med* 382:1679–1681. <https://doi.org/10.1056/NEJMp2003539>
- Khera R, Jain S, Lin Z, Ross JS, Krumholz H (2020) Evaluation of the Anticipated Burden of COVID-19 on Hospital-Based Healthcare Services Across the United States. *medRxiv*. <https://doi.org/10.1101/2020.04.01.20050492>
- Martínez-Pérez B, de la Torre-Díez I (2014) Mobile Clinical Decision Support Systems and Applications : A Literature and

- Commercial Review. *Journal of medical systems* 38:4. <https://doi.org/10.1007/s10916-013-0004-y>
25. Iorio-Morin C, Fortin D, Blanchard J (2016) TBI prognosis calculator: A mobile application to estimate mortality and morbidity following traumatic brain injury. *Clin Neurol Neurosurg* 142:48–53. <https://doi.org/10.1016/j.clineuro.2016.01.021>
  26. Cohen AB, Nahed BV, Sheth KN (2013) Mobile medical applications in neurology. *Neurol Clin Pr* 3:52–60. <https://doi.org/10.1212/CPJ.0b013e318283ff4f>
  27. Choi W, Park MA, Hong E, Kim S, Ahn R, Hong J, Song S, Kim T, Kim J, Yeo S (2013) Development of mobile electronic health records application in a secondary general hospital in Korea. *Healthc Inform Res* 19:307–313. <https://doi.org/10.4258/hir.2013.19.4.307>
  28. Hansen C, Sanchez-Ferro A, Maetzler W (2018) How mobile health technology and electronic health records will change care of patients with Parkinson's disease. *J Parkinsons Dis* 8:S41–S45. <https://doi.org/10.3233/JPD-181498>
  29. Choi W, Park M, Hong E, Kim S, Ahn R, Hong J, Song S, Kim T, Kim J, Yeo S (2015) Early experiences with mobile electronic health records application in a tertiary hospital in Korea. *Healthc Inform Res* 21:292–298. <https://doi.org/10.4258/hir.2015.21.4.292>
  30. Peters AW, Chawla KS, Turnbull ZA (2020) Transforming ORs into ICUs. *N Engl J Med*, 382(19): p.e52. <https://doi.org/10.1056/NEJMc2010853>
  31. Carmona MJ, Quintão VC, Melo BF, André RG, Kayano RP, Perondi B, Miethke-Morais A, Rocha MC, Malbouisson LM, Auler-Júnior JO (2020) Transforming operating rooms into intensive care units and the versatility of the physician anesthesiologist during the COVID-19 crisis. *Clinics*, 12(75): e2023. <https://doi.org/10.6061/clinics/2020/e2023>
  32. Qiu H, Tong Z, Ma P, Hu M, Peng Z, Wu W, Du B (2020) Intensive care during the coronavirus epidemic. *Intensive Care Med* 46:576–578. <https://doi.org/10.1007/s00134-020-05966-y>
  33. Pan L, Wang L, Huang X (2020) How to face the novel coronavirus infection during the 2019 – 2020 epidemic : the experience of Sichuan Provincial People ' s Hospital. *Intensive Care Med* 46:573–575. <https://doi.org/10.1007/s00134-020-05964-0>
  34. Liao X, Wang B, Kang Y (2020) Novel coronavirus infection during the 2019 – 2020 epidemic : preparing intensive care units — the experience in Sichuan Province , China. *Intensive Care Med* 46:357–360. <https://doi.org/10.1007/s00134-020-05954-2>
  35. Polit DF, Beck CT (2009) *Essentials of Nursing Research: Appraising Evidence for Nursing Practice*. Lippincott Williams & Wilkins
  36. Moher D, Liberati A, Tetzlaff J, Altman DG, The PRISMA Group (2009) Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS Med* 6:e1000097. <https://doi.org/10.1371/journal.pmed.1000097>
  37. iPadian Premium - The Best iOS and iPad simulator. <https://ipadian.net/>. Accessed 10 August 2020
  38. Stoyanov SR, Hides L, Kavanagh DJ, Wilson H (2016) Development and Validation of the User Version of the Mobile Application Rating Scale (uMARS). *JMIR mHealth uHealth* 4:e72. <https://doi.org/10.2196/mhealth.5849>
  39. Team RC (2013) R version 3.6. 0. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna. <https://doi.org/10.1002/nur.21990>
  40. Johnson AEW, Pollard TJ, Shen L, Lehman LH, Feng M, Ghassemi M, Moody B, Szolovits P, Celi LA, Mark RG (2016) MIMIC-III , a freely accessible critical care database. *Scientific data* 3:1–9. <https://doi.org/10.1038/sdata.2016.35>
  41. Vincent JL, Moreno R, Takala J, Willatts S, De Mendonça A, Bruining H, Reinhart CK, Suter P, Thijs LG (1996) The SOFA (Sepsis-related Organ Failure Assessment) score to describe organ dysfunction/failure. *Intensive Care Med* 22(7):707–10. <https://doi.org/10.1007/BF01709751>
  42. Adam A, Hellig JC, Perera M, Bolton D, Lawrentschuk N (2018) 'Prostate Cancer Risk Calculator' mobile applications (Apps): a systematic review and scoring using the validated user version of the Mobile Application Rating Scale (uMARS). *World Journal of Urology*. Apr;36(4):565–73. <https://doi.org/10.2196/mhealth.5882>
  43. Bardou M, Ali A, Demachkieh F, Hamadeh G (2019) Assessing the quality of mobile phone apps for weight management: User-centered study with employees from a Lebanese university. *JMIR mHealth uHealth* 7: e9836. <https://doi.org/10.2196/mhealth.9836>
  44. Li Y, Ding J, Wang Y, Tang C, Zhang P (2019) Nutrition-related mobile apps in the China App Store: Assessment of functionality and quality. *JMIR mHealth uHealth* 7:e13261. <https://doi.org/10.2196/13261>
  45. Fijačko N, Gosak L, Cilar L, Novšak A, Creber RM, Skok P, Štiglic G (2019) The Effects of Gamification and Oral Self-Care on Oral Hygiene in Children: Systematic Search in App Stores and Evaluation of Apps . *JMIR mHealth uHealth* 8:e16365. <https://doi.org/10.2196/16365>
  46. Lebeau K, Huey LG, Hart M (2019) Assessing the quality of mobile apps used by occupational therapists: Evaluation using the user version of the mobile application rating scale. *JMIR mHealth uHealth* 7:e13019. <https://doi.org/10.2196/13019>
  47. Pettilä V (2002) Sequential assessment of multiple organ dysfunction as a predictor of outcome. *JAMA* 287:713–714. <https://doi.org/10.1001/jama.287.6.711>
  48. Seymour CW, Liu VX, Iwashyna TJ, Brunkhorst FM, Rea TD, Scherag A, Rubenfeld G, Kahn JM, Shankar-Hari M, Singer M, Deutschman CS (2016) Assessment of clinical criteria for sepsis for the third international consensus definitions for sepsis and septic shock (sepsis-3). *JAMA* 315:762–774. <https://doi.org/10.1001/jama.2016.0288>
  49. Knaus WA, Draper EA, Wagner DP, Zimmerman JE (1985) APACHE II: a severity of disease classification system. *Crit Care Med* 13(10):818–829. <https://doi.org/10.1097/00003465-198603000-00013>
  50. Knaus WA, Wagner DP, Draper EA, Zimmerman JE, Bergner M, Bastos PG, Sirio CA, Murphy DJ, Lotring T, Damiano A, Harrell Jr FE (1991) The APACHE III prognostic system: Risk prediction of hospital mortality for critically III hospitalized adults. *Chest* 100:1619–1636. <https://doi.org/10.1378/chest.100.6.1619>
  51. Knaus WA, Zimmerman JE, Wagner DP, Draper EA, Lawrence DE (1981) APACHE-acute physiology and chronic health evaluation: a physiologically based classification system. *Crit Care Med* 9:591–597. <https://doi.org/10.1097/00003246-198108000-00008>
  52. Zimmerman JE, Kramer AA, McNair DS, Malila FM (2006) Acute Physiology and Chronic Health Evaluation (APACHE) IV: Hospital mortality assessment for today's critically ill patients. *Crit Care Med* 34:1297–1310. <https://doi.org/10.1097/01.CCM.0000215112.84523.F0>
  53. Smith GB, Prytherch DR, Meredith P, Schmidt PE, Featherstone PI. The ability of the National Early Warning Score (NEWS) to discriminate patients at risk of early cardiac arrest, unanticipated intensive care unit admission, and death. *Resuscitation* 84:465–470. <https://doi.org/10.1016/j.resuscitation.2012.12.016>
  54. Raoyal College of Physicians (2017) National Early Warning Score (NEWS) 2. <https://www.rplondon.ac.uk/projects/outputs/national-early-warning-score-news-2> Accessed 10 August 2020
  55. Subbe CP, Kruger M, Rutherford P, Gemmel L (2001) Validation of a modified early warning score in medical admissions. *QJM* 94:521–526. <https://doi.org/10.1093/qjmed/94.10.521>
  56. Marshall JC, Cook DJ, Christou NV, Bernard GR, Sprung CL, Sibbald WJ (1995) Multiple organ dysfunction score: a reliable descriptor of

- complex clinical outcome. *Crit Care Med* 23(10):1638–1652. <https://doi.org/10.1097/00003246-199510000-00007>
57. Le Gall JR, Loirat P, Alperovitch A, Glaser P, Granthil C, Mathieu D, Mercier P, Thomas R, Villers D (1984) A simplified acute physiology score for ICU patients. *Crit Care Med* 12:975–977. <https://doi.org/10.1097/00003246-198411000-00012>
  58. Moreno RP, Metnitz PGH, Almeida E, Jordan B, Bauer P, Campos RA, Iapichino G, Edbrooke D, Capuzzo M, Le Gall JR, SAPS 3 Investigators (2005) SAPS 3 - From evaluation of the patient to evaluation of the intensive care unit. Part 2: Development of a prognostic model for hospital mortality at ICU admission. *Intensive Care Med* 31:1345–1355. <https://doi.org/10.1007/s00134-005-2763-5>
  59. Le Gall JR, Lemeshow S, Saulnier F (1993) A new Simplified Acute Physiology Score (SAPS II) based on a European/North American multicenter study. *Jama* 270:2957–2963. <https://doi.org/10.1001/jama.270.24.2957>
  60. Bone RC, Balk RA, Cerra FB, Dellinger RP, Fein AM, Knaus WA, Schein RM, Sibbald WJ (1992) Definitions for sepsis and organ failure and guidelines for the use of innovative therapies in sepsis. *Chest* 101:1644–1655. <https://doi.org/10.1378/chest.101.6.1644>
  61. Balk RA (2014) Systemic inflammatory response syndrome (SIRS): Where did it come from and is it still relevant today? *Virulence* 5:20–26. <https://doi.org/10.4161/viru.27135>
  62. Singer M, Deutschman CS, Seymour C, Shankar-Hari M, Annane D, Bauer M, Bellomo R, Bernard GR, Chiche JD, Coopersmith CM, Hotchkiss RS (2016) The third international consensus definitions for sepsis and septic shock (sepsis-3). *JAMA* 315:801–810. <https://doi.org/10.1001/jama.2016.0287>
  63. Le Gall JR, Klar J, Lemeshow S, Saulnier F, Alberti C, Artigas A, Teres D (1996) The Logistic Organ Dysfunction system: a new way to assess organ dysfunction in the intensive care unit. *Jama* 276:802–810. <https://doi.org/10.1001/jama.276.10.802>
  64. Lemeshow S, Teres D, Klar J, Avrunin JS, Gehlbach SH, Rapoport J (1993) Mortality Probability Models (MPM II) based on an international cohort of intensive care unit patients. *Jama* 270:2478–2486. PMID: 8230626
  65. Olsson T, Terent A, Lind L (2004) Rapid Emergency Medicine Score can predict long-term mortality in nonsurgical emergency department patients. *Acad Emerg Med* 11(10):1008–1013. <https://doi.org/10.1197/j.aem.2004.05.027>
  66. Providência R, Boveda S, Lambiase P, Defaye P, Algalarrondo V, Sadoul N, Piot O, Klug D, Perier MC, Bouzeman A, Gras D (2015) Prediction of nonarrhythmic mortality in primary prevention implantable cardioverter-defibrillator patients with ischemic and nonischemic cardiomyopathy. *JACC Clin Electrophysiol* 1:29–37. <https://doi.org/10.1016/j.jacep.2015.01.004>
  67. Zapata BC, Fernández-Alemán JL, Idri A, Toval A (2015) Empirical Studies on Usability of mHealth Apps: A Systematic Literature Review. *J Med Syst* 39:1–19. <https://doi.org/10.1007/s10916-014-0182-2>
  68. Collado-Borrell R, Escudero-Vilaplana V, Ribed-Sánchez A, Ibáñez-García S, Herranz-Alonso A, Sanjurjo-Sáez M (2016) Smartphone applications for cancer patients; what we know about them? *Farm Hosp* 40:25–35. <https://doi.org/10.7399/fh.2016.40.1.8993>
  69. Fijacko N, Brzan PP, Stiglic G (2015) Mobile Applications for Type 2 Diabetes Risk Estimation: a Systematic Review. *J Med Syst* 39:124. <https://doi.org/10.1007/s10916-015-0319-y>
  70. Sillence E, Briggs P, Harris PR, Fishwick L (2007) How do patients evaluate and make use of online health information? *Soc Sci Med* 64:1853–1862. <https://doi.org/10.1016/j.socscimed.2007.01.012>
  71. NHS. <https://www.nhs.uk/>. Accessed 10 August 2020
  72. ORCHA. <https://www.orchac.co.uk/>. Accessed 10 August 2020
  73. Weiss P, Murdoch DR (2020). Clinical course and mortality risk of severe COVID-19. *Lancet* 395:1014–1015. [https://doi.org/10.1016/S0140-6736\(20\)30633-4](https://doi.org/10.1016/S0140-6736(20)30633-4)
  74. Zhang G, Hu C, Luo L, Fang F, Chen Y, Li J, Peng Z, Pan H (2020) Clinical features and short-term outcomes of 221 patients with COVID-19 in Wuhan, China. *J Clin Virol* 127:104364. <https://doi.org/10.1016/j.jcv.2020.104364>
  75. Zhou F, Yu T, Du R, Fan G, Liu Y, Liu Z, Xiang J, Wang Y, Song B, Gu X, Guan L (2020) Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study. *Lancet* 395:1054–1062. [https://doi.org/10.1016/S0140-6736\(20\)30566-3](https://doi.org/10.1016/S0140-6736(20)30566-3)
  76. Yan L, Zhang H-T, Goncalves J, Xiao Y, Wang M, Guo Y, Sun C, Tang X, Jin L, Zhang M, Huang X. A machine learning-based model for survival prediction in patients with severe COVID-19 infection. medRxiv 2020. <https://doi.org/10.1101/2020.02.27.20028027>
  77. Lu J, Hu S, Fan R, Liu Z, Yin X, Wang Q, Lv Q, Cai Z, Li H, Hu Y, Han Y (2020) ACP risk grade: a simple mortality index for patients with confirmed or suspected severe acute respiratory syndrome coronavirus 2 disease (COVID-19) during the early stage of outbreak in Wuhan, China. <https://doi.org/10.1101/2020.02.20.20025510>
  78. Qin C, Zhou L, Hu Z, Zhang S, Yang S, Tao Y, Xie C, Ma K, Shang K, Wang W, Tian DS (2020) Dysregulation of immune response in patients with COVID-19 in Wuhan, China. *Clin Infect Dis* 71:762–768. <https://doi.org/10.1093/cid/ciaa248>
  79. Lagunas-Rangel FA (2020) Neutrophil-to-lymphocyte ratio and lymphocyte-to-C-reactive protein ratio in patients with severe coronavirus disease 2019 (COVID-19): A meta-analysis. *J Med Virol*. 2020:1-2. <https://doi.org/10.1002/jmv.25819>
  80. Liu Y, Du X, Chen J, Jin Y, Peng L, Wang HH, Luo M, Chen L, Zhao Y. Neutrophil-to-lymphocyte ratio as an independent risk factor for mortality in hospitalized patients with COVID-19. *J Infect* 81:e6–e12. <https://doi.org/10.1016/j.jinf.2020.04.002>
  81. Worku B, Gaudino M, Avgerinos D, Ramasubbu K, Gambardella I, Gulkarov I, Khin S. A comparison of existing risk prediction models in patients undergoing venoarterial extracorporeal membrane oxygenation. *Heart & Lung*. <https://doi.org/10.1016/j.hrtlng.2020.03.004>
  82. Rello J, Tejada S, Userovici C, Arvaniti K, Pugin J, Waterer G (2020) Coronavirus Disease 2019 (COVID-19): A critical care perspective beyond China. *Anaesth Crit Care Pain Med* 39:167–169. <https://doi.org/10.1016/j.accpm.2020.03.001>
  83. Jin X, Pang B, Zhang J, Liu Q, Yang Z, Feng J, Liu X, Zhang L, Wang B, Huang Y, Fauci AJ. Core Outcome Set for Clinical Trials on Coronavirus Disease 2019 (COS-COVID). *Engineering*. <https://doi.org/10.1016/j.eng.2020.03.002>
  84. Qiu R, Wei X, Zhao M, Zhong C, Zhao C, Hu J, Li M, Huang Y, Han S, He T, Chen J (2020) Outcome reporting from protocols of clinical trials of Coronavirus Disease 2019 (COVID-19): a review. medRxiv <https://doi.org/10.1101/2020.03.04.20031401>
  85. Jamil S, Mark N, Carlos G, Cruz CSD, Gross JE, Pasnich S (2020) Diagnosis and Management of COVID-19 Disease. *Am J Respir Crit Care Med* 201:P19–P20. <https://doi.org/10.1164/rccm.2020C1>
  86. Truog RD, Mitchell C, Daley GQ (2020) The toughest triage—allocating ventilators in a pandemic. *N Engl J Med* 382:1969–1973. <https://doi.org/10.1056/NEJMp2005689>
  87. Aziz S, Arabi YM, Alhazzani W, Evans L, Citerio G, Fischkoff K, Salluh J, Meyfroidt G, Alshamsi F, Oczkowski S, Azoulay E (2014) Managing ICU surge during the COVID-19 crisis: rapid guidelines. *Intensive Care Med* 46:1303–1325. <https://doi.org/10.1007/s00134-020-06092-5>
  88. Yu S, Leung S, Heo M, Soto GJ, Shah RT, Gunda S, Gong MN (2014) Comparison of risk prediction scoring systems for ward patients: A retrospective nested case-control study. *Crit Care* 18:R132. <http://ccforum.com/content/18/3/R132>
  89. Arie S (2020) Covid-19: Can France’s ethical support units help doctors make challenging decisions? *BMJ* 369:2–3. <https://doi.org/10.1136/bmj.m1291>