SUPPLEMENTARY MATERIAL

Supplementary Box: Search algorithm in Pubmed.

Supplementary Figure 1: Study-selection flowchart of AI-RCTs (protocols and published reports).

Supplementary Table 1: General characteristics of published protocols and completed RCTs evaluating artificial intelligence tools. Studies are ordered by year of publication and also grouped based on the indexed AI tool.

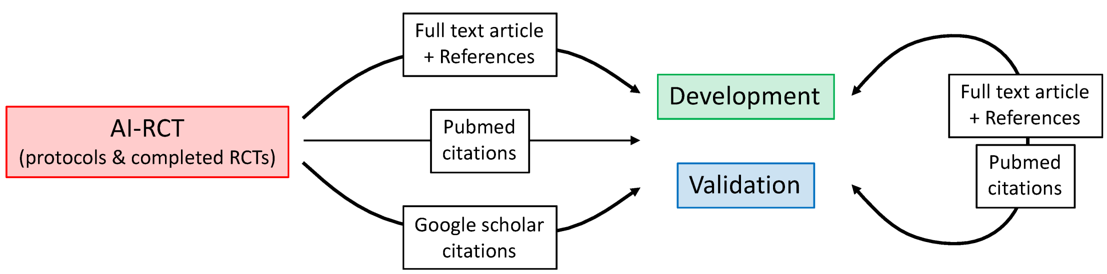
Supplementary Table 2: Information related to data management and assessed outcome(s).

Supplementary Table 3: Risk of Bias assessment for each AI-RCT by using the revised Cochrane risk-of-bias tool for randomized trials Risk of Bias (RoB) 2 (Sterne J et al. BMJ. 2019).

Supplementary Table 4: Summary of peer-reviewed studies in which the indexed AI tool was developed and externally validated. Studies are ordered according to the time of the corresponding AI-RCT protocol/report publication and grouped by the indexed AI tool.

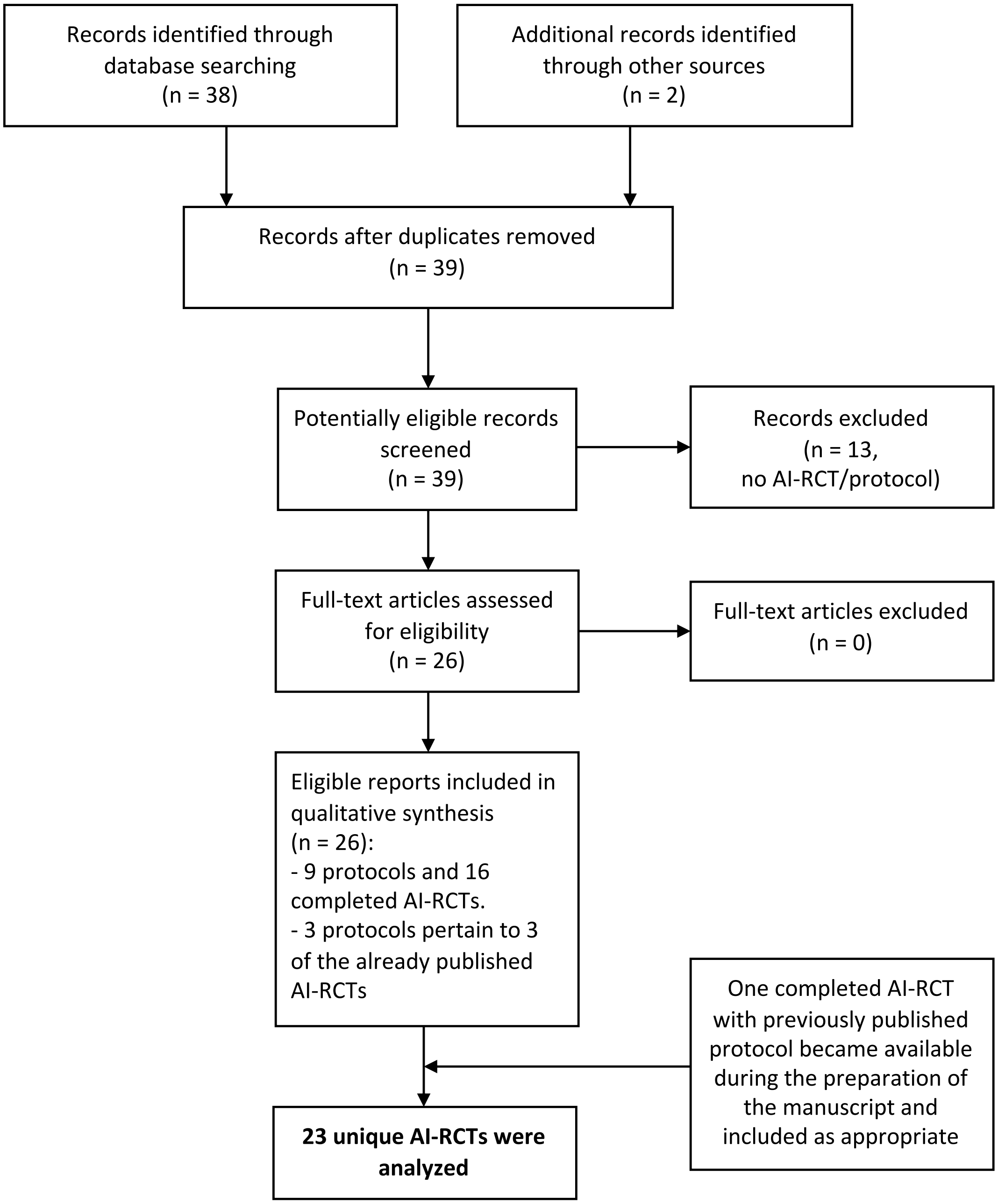
Supplementary Box: Search algorithm in Pubmed and strategies for identification of peer reviewed studies of development and validation of AI tools evaluated in protocols/completed AI-RCTs.

1. (artificial intelligence*[tiab] OR machine learning[tiab] OR neural network*[tiab] OR deep learning[tiab] OR cognitive computing[tiab] OR computer vision[tiab] OR natural language processing[tiab])
2. (random*[tiab] OR protocol*[tiab] OR study design*[tiab])
3. 1 and 2
4. Limit 3 to yr = 2000-nowadays



Siontis GCM, *et al. BMJ Health Care Inform* 2021; 28:e100466. doi: 10.1136/bmjhci-2021-100466

Supplementary Figure 1: Study-selection flowchart of AI-RCTs (protocols and published reports).



Supplementary Table 1: General characteristics of published protocols and completed RCTs evaluating artificial intelligence tools. Studies are ordered by year of publication and also grouped based on the specific AI tool.

First author, year of publication	Type of report	Geographic area / Trial's sites / N. arms	Level of randomization	Power calculations	Sample size	Experimental AI-based intervention	Control intervention	Medical condition	Recruitment period	Funding source	Follow-up duration	Access to code
El-Solh A. et al., 2009[20]	AI-RCT	North America / Single center / 2	Patients	Power 80%, type I error of 5% assuming 20% reduction in time to optimal CPAP	115	Artificial neural network-guided continuous positive airway pressure titration	Conventional continuous positive airway pressure titration	Obstructive sleep apnea	Not reported	None reported	1 month	No
Martin C., et al., 2012[21]	AI-RCT	Europe / Multicenter / 2	Patients	Not applicable	214	Patient journey system: machine learning and ruled-based algorithms to analyze answers to questions on health status	Standard of care	Older patients with chronic illness	November 2010 to December 2011	None reported	Diverse across individuals	No
Zeevi D., et al. 2015[22]	AI-RCT	Other / Multicenter / 2	Patients	Not applicable	100	Machine-learning algorithm to predict personalized postprandial glycemic response to real-life meals	Clinical experts	Healthy and prediabetic individuals	Not reported	None reported	2 weeks	No

Piette J., et al. 2016[23]	Protocol	North America / Multicenter / 2	Patients	Power 90%, type I error (1-sided) of 2.5% to detect noninferiority within a margin of 2 points (SD 4.5)	320	Artificial intelligence based cognitive behavioral therapy	Standard telephone cognitive behavioral therapy	Patients with chronic low back pain	Begin in the fall of 2016	Non-industry related	6 months	No
Sadasivam R., et al. 2016[24]	AI-RCT	North America / Multicenter / 2	Patients	Not applicable	120	Machine learning computer-tailored health communication system	Standard rule-based computer-tailored health communication system	Current smokers	October 2014 to January 2015	Non-industry related	1 month	No
Shimabukuro D., et al. 2017[25]	AI-RCT	North America / Single center / 2	Patients	Power 80%, type I error of 5% to detect a reduction of 1.5 days in hospital length of stay	142	Machine learning algorithm for severe sepsis detection	Standard electronic health record-based severe sepsis detector	Patients admitted to intensive care unit	December 2016 to February 2017	Non-industry related	Until hospital discharge	No

Fulmer R., et al. 2018[26]	AI-RCT	North America / Multicenter / 2	Patients	Not applicable	75	Integrative psychological artificial intelligence chatbot tool (Tess)	Information-only control group received an electronic link to the NIMH's eBook on depression among college students	College students at risk of depression and anxiety	Not reported	None reported	2 and 4 weeks	No
Popp C., et al. 2019[27]	Protocol	North America / Single center / 2	Patients	Power 80%, type I error of 5% to detect 2% difference in weight loss	200	Personalized dietary intervention based on estimation of glycemic response to meal by machine learning	Low fat diet	Overweight adults with pre-diabetes and type 2 diabetes mellitus	January 2018 to December 2019	Non-industry related	12 months	No
Wang P., et al. 2019[28]	AI-RCT	Asia / Single center / 2	Patients	Power 80%, type I error of 5% to detect 10% difference in adenoma detection rate	1130	Colonoscopy with an automatic real-time polyp detection system based on deep learning	Standard diagnostic colonoscopy	Patients referred to colonoscopy	September 2017 to February 2018	None reported	Real-time automatic polyp detection	No

Wu L., et al. 2019[29]	AI-RCT	Asia / Single center / 2	Patients	Power 90%, type I error of 5% to detect 0.1 difference in blind spot rate detection (superiority margin 0.05)	324	Artificial intelligence (WISENSE) assisted esophagogastroduodenoscopy	Unassisted esophagogastroduodenoscopy	Patients undergoing esophagogastroduodenoscopy	August 2018 to October 2018	Non-industry related	None	No
Oka R., et al. 2019[30]	Protocol	Asia / Multicenter / 2	Patients	Power 80%, type I error of 5% to detect 0.3% mean change in HbA1c level (non-inferiority margin 0.2%)	100	Artificial intelligence supported nutrition therapy	Human nutrition therapy	Patients with type 2 diabetes mellitus mainly controlled with diet	April 2018 to April 2020	Non-industry related	12 months	No
Lin H., et al. 2019[31]	AI-RCT	Asia / Multicenter / 2	Patients	Power 80%, type I error of 5% to detect 5% difference in diagnostic accuracy	350	Artificial intelligence based diagnosis and treatment recommendation	Opthalmologist based diagnosis and treatment	Pediatric patients (<14 years) without known cataract	August 2017 to May 2018	Non-industry related	Not applicable	No

Wang P., et al. 2020[32]	AI-RCT	Asia / Single center / 2	Patients	Power 80%, type I error of 5% to detect 10% increase in adenoma detection rate	1046	Computer aided colonoscopy using artificial intelligence	Unassisted colonoscopy with sham control system (artificial intelligence model with intentional lower sensitivity and specificity)	Patients undergoing colonoscopy	September 2018 to January 2019	None	Real-time	No
Chen D., et al. 2020[33]	AI-RCT	Asia / Single center / 3	Patients	Power 90%, 2-sided alpha of .0167 (type I error 1.67%); based on pilot data	437	Sedated (1) or unsedated (2) esophagogastroduodenoscopy or unsedated ultrathin transoral endoscopy (3) with artificial intelligence assistance	Sedated (1) or unsedated (2) esophagogastroduodenoscopy or unsedated ultrathin transoral endoscopy (3) without artificial intelligence assistance	Patients undergoing esophagogastroduodenoscopy	January 2019 to February 2019	None reported	None	No
Gong D., et al. 2020[34]	AI-RCT	Asia / Single center / 2	Patients	Power 80%, type I error of 5% to detect 8% increase in adenoma detection rate	704	Artificial intelligence (deep neural networks and perceptual hash algorithms) enhanced colonoscopy	Unassisted colonoscopy	Patients undergoing colonoscopy	June 2019 to September 2019	Non-industry related	Diverse across individuals, every 4 weeks until September 6th, 2019; median 18 days	No

Wijnberge M., et al. 2020[35,36]	Protocol / AI-RCT	Europe / Single center / 2	Patients	Power 80%, type I error of 5% to detect 75% reduction of hypotension in terms of depth and duration (time-weighted average of 0.38 +/- 0.51)	68	Artificial intelligence powered early hypotension detection	Standard of care	Patients undergoing elective non-cardiac surgery under general anesthesia requiring arterial line	May 2018 to March 2019	Industry related	Perioperative	No
Schneck E., et al. 2020[37]	AI-RCT	Europe / Single center / 2	Patients	Not applicable	50	Artificial intelligence guided hypotension management	Standard of care	Adult patients undergoing total hip arthroplasty	July 2017 to August 2018	Industry related	Perioperative	No
Maheshwari K., et al. 2020[38,39]	Protocol / AI-RCT	North America / Multicenter / 2	Patients	Power 80%, type I error of 5% to detect 20% reduction of hypotension (AUC-MAP <65mmHg)	214	Artificial intelligence guided hypotension management	Standard of care	Adult patients (>44 years) undergoing elective non-cardiac surgery under general anesthesia requiring arterial line	July 2018 to April 2019	Industry related	30 days	No
Auloge P., et al. 2020[40]	AI-RCT	Europe / Single center / 2	Patients	Power 80%, type I error of 5% to detect 2.0 +/- 1.5mm difference in trocar	20	Augmented reality/artificial intelligence guided trocar insertion	Fluoroscopy guided trocar insertion	Patients undergoing single-level vertebroplasty	January 2018 to April 2018	None	Real-time	No

				placement accuracy								
Wong C., et al. 2020[41]	Protocol	Asia / Multicenter / 2	Patients	Sample size will be determined based on the result from the phase I run-in period involving approximately 100 subjects	200-1000	Artificial intelligence powered remote physiological monitoring	Self temperature monitoring	Asymptomatic subjects with COVID-19 exposure	Not reported	None reported	14 days	No
Aguilera A., et al. 2020[42]	Protocol	North America / Multicenter / 3	Patients	Power 80% to detect mean increase of 1250 steps	276	Adaptive text messages using artificial intelligence (reinforcement learning)	Non-adaptive text messages (random)	Diabetes and depression	Not reported	Non-industry related	6 months	No
Hill N., et al. 2020[43]	Protocol	Europe / Multicenter / 2	Patients	Power 88.5%, type I error of 5% to detect 1.7% difference in atrial fibrillation diagnosis rate	18000	Artificial intelligence guided atrial fibrillation screening	Standard of care	Adult patients (>30 years) without known atrial fibrillation	First participant enrolled August 2019	Industry related	3 years	No

Yao X., et al. 2021[44,45]	Protocol / AI-RCT	North America / Multicenter / 2	Clinicians	Power 80% to increase low left ventricular ejection fraction detection rate from 2.4 to 3.45-4.06%	22641	Artificial intelligence based ECG screening for left ventricular ejection fraction <50%	Standard of care	Patients without known LV-EF reduction (<50%) receiving ECG in a primary care setting	August 2019 to March 2020 (patients' recruitment period)	Non-industry related	90 days	Upon request

Supplementary Table 2: Information related to data management and assessed outcome(s).

First author, year of publication	Data collection method	Strategies dealing with missing data	Single or composite primary outcome	Primary outcome	Type of primary outcome	Outcome adjudication method	Primary outcome favors AI-tool
El-Solh A. et al., 2009[20]	Not specified	Not specified	Single	Time of achieving optimal continuous positive airway pressure titration	Continuous	Not specified	Yes
Martin C., et al., 2012[21]	Not specified	Not specified	Single	Unplanned emergency ambulatory care sensitive admissions	Binary	Not specified	Yes
Zeevi D., et al. 2015[22]	Not specified	Not specified	Single	Postprandial glycemic responses	Continuous	Not specified	Yes
Piette J., et al. 2016[23]	Dedicated personnel & Electronic health records	Multiple imputation methods if >15% of a covariate is missing	Single	24-item Roland Morris Disability Questionnaire (RMDQ)	Categorical	Not specified	Not applicable
Sadasivam R., et al. 2016[24]	Not specified	Not specified	Single	Smoking cessation	Binary	Not specified	Yes
Shimabukuro D., et al. 2017[25]	Electronic health records	Not specified	Single	Average hospital length of stay	Continuous	Not specified	Yes
Fulmer R., et al. 2018[26]	Dedicated personnel & Electronic health records	Not specified	Single	Self-report tools (PHQ-9, GAD-7, PANAS) for symptoms	Continuous	Not specified	Yes

				of depression and anxiety			
Popp C., et al. 2019[27]	Dedicated personnel	Identification of predictors for missing data during preliminary analysis phase, subsequently included as covariates under assumption of missing at random	Single	Body weight loss	Continuous	Not applicable	Not applicable
Wang P., et al. 2019[28]	Not specified	Not specified	Single	Adenoma detection rate	Binary	Not specified	Yes
Wu L., et al. 2019[29]	Not applicable	Not specified	Single	Blind spot rate	Continuous	Not specified	Yes
Oka R., et al. 2019[30]	Electronic health records	Use of mixed models	Single	Change in glycated hemoglobin levels	Continuous	Not applicable	Not applicable
Lin H., et al. 2019[31]	Not applicable	Not specified	Single	Diagnostic performance for childhood cataract	Binary	Diagnosis by cataract experts	No
Wang P., et al. 2020[32]	Dedicated personnel	Not specified	Single	Adenoma detection rate	Binary	Not specified	Yes
Chen D., et al. 2020[33]	Not applicable	Not specified	Single	Blind spot rate	Continuous	Not specified	Yes
Gong D., et al. 2020[34]	Not specified	Not specified	Single	Adenoma detection rate	Continuous	Not specified	Yes

Wijnberge M., et al. 2020[35,36]	Dedicated personnel	Not specified	Single	Time-weighted average of hypotension during surgery	Continuous	Not specified	Yes
Schneck E., et al. 2020[37]	Dedicated personnel	Not specified	Single	Frequency and absolute and relative duration of intraoperative hypotension	Binary, continuous	Not specified	Yes
Maheshwari K., et al. 2020[38,39]	Dedicated personnel & Electronic health records	Not specified	Single	Time-weighted average of hypotension during surgery	Continuous	Not specified	No
Auloge P., et al. 2020[40]	Not applicable	Not specified	Single	Technical feasibility of trocar placement using augmented reality/artificial intelligence guidance	Binary	Not specified	Not applicable (no comparison for the primary outcome, primary secondary outcome (used for power calculation) equipoise)
Wong C., et al. 2020[41]	Dedicated personnel	Not specified	Single	Time to diagnosis of coronavirus disease 19	Continuous	Not applicable	Not applicable
Aguilera A., et al. 2020[42]	Dedicated personnel & Electronic health records	Full-information maximum likelihood, including patients that have at least 1 month of data available	Single	Improvement in physical activity defined by daily step counts	Continuous	Not applicable	Not applicable

Hill N., et al. 2020[43]	Electronic health records	Not specified	Single	Prevalence of diagnosed atrial fibrillation	Continuous	Not specified	Not applicable
Yao X., et al. 2021[44,45]	Electronic health records	Not specified	Single	Newly discovered left ventricular ejection fraction <50%	Binary	Not specified	Yes

Supplementary Table 3: Risk of Bias assessment for each AI-RCT by using the revised Cochrane risk-of-bias tool for randomized trials Risk of Bias (RoB) 2 (Sterne J et al. BMJ. 2019).

First author, year of publication	**1. Bias arising from the randomisation process**	**2. Bias due to deviations from intended interventions**	**3. Bias due to missing outcome data**	**4. Bias in measurement of the outcome**	**5. Bias in selection of the reported result**	**Overall**
El-Sohl A. et al., 2009 [19259717]	low risk of bias	some concerns	low risk of bias	low risk of bias	some concerns	**some concerns**
Marti C., et al., 2012 [22816797]	high risk of bias	some concerns	high risk of bias	high risk of bias	some concerns	**high risk of bias**
Zeevi D., et al. 2015 [26590418]	some concerns	high risk of bias	high risk of bias	low risk of bias	some concerns	**high risk of bias**
Sadasivam R., et al. 2016 [27826134]	low risk of bias	some concerns	high risk of bias	low risk of bias	some concerns	**high risk of bias**
Shimabukuro D., et al. 2017 [29435343]	low risk of bias	some concerns	low risk of bias	low risk of bias	some concerns	**some concerns**
Fulmer R., et al. 2018 [30545815]	low risk of bias	high risk of bias	low risk of bias	high risk of bias	high risk of bias	**high risk of bias**
Wang P., et al. 2019 [30814121]	low risk of bias	high risk of bias	low risk of bias	high risk of bias	some concerns	**high risk of bias**
Wu L., et al. 2019 [30858305]	low risk of bias	high risk of bias	low risk of bias	high risk of bias	low risk of bias	**high risk of bias**
Lin H., et al. 2019 [31143882]	low risk of bias	low risk of bias	low risk of bias	low risk of bias	low risk of bias	**low risk of bias**
Wang P., et al. 2020 [31981517]	low risk of bias	high risk of bias	low risk of bias	high risk of bias	low risk of bias	**high risk of bias**
Chen D., et al. 2020 [31541626]	low risk of bias	some concerns	low risk of bias	low risk of bias	low risk of bias	**some concerns**

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Gong D., et al. 2020 [31981518]	low risk of bias	low risk of bias	low risk of bias	low risk of bias	low risk of bias	**low risk of bias**
Wijnberge M., et al. 2020 [31601239; 32065827]	low risk of bias	high risk of bias	low risk of bias	low risk of bias	low risk of bias	**high risk of bias**
Schneck E., et al. 2020 [31784852]	low risk of bias	some concerns	low risk of bias	low risk of bias	low risk of bias	**some concerns**
Maheshwari K., et al. 2020 [31053082; 32960954]	low risk of bias	some concerns	low risk of bias	low risk of bias	low risk of bias	**some concerns**
Auloge P., et al. 2020 [31270676]	some concerns	some concerns	low risk of bias	high risk of bias	some concerns	**high risk of bias**
Yao X., et al. 2019 [31710842]	low risk of bias	low risk of bias	low risk of bias	low risk of bias	low risk of bias	**low risk of bias**

Supplementary Table 4: Summary of peer-reviewed studies in which the indexed AI-tool was developed and externally validated. Studies are ordered according to the time of the corresponding AI-RCT protocol/report publication and grouped by the indexed AI tool.

	Development studies				External validation studies			
Protocol/completed AI-RCT	**First author, year of publication**	**Geographic area**	**Sample size**	**Recruitment period**	**First author, year of publication**	**Geographic area**	**Sample size**	**Recruitement period**
El-Solh A. et al., 2009[20]	El-Sohl A. et al., 2007[S1]	North America	311	Jan 2005 to Aug 2005	-	-	-	-
Martin C., et al., 2012[21]	-	-	-	-	-	-	-	-
Zeevi D., et al. 2015[22]	Zeevi D., et al. 2015[22]	Other	800	not reported	Zeevi D., et al. 2015[22]	Other	100	not reported
					Mendes-Soares H., et al. 2019[S2]	North America	327	Oct 2016 to Dec 2017
Piette J., et al. 2016[23]	-	-	-	-	-	-	-	-
Sadasivam R., et al. 2016[24]	-	-	-	-	Faro J., et al. 2020[S3]	North America	55	Apr 2017 to Nov 2017
Shimabukuro D., et al. 2017[25]	Calvert J., et al. 2016[S4]	North America	1394	2001 to 2008	McCoy A., et al. 2017[S5]	North America	1328	Feb 2017 to Apr 2017
					Mao Q., et al. 2018[S6]	North America	90353	Jun 2011 to Mar 2016
Fulmer R., et al. 2018[26]	-	-	-	-	Stephens T., et al. 2019[S7]	North America	23	not reported
					Green E., et al. 2020[S8]	Other	41	not reported

Popp C., et al. 2019[27]	Zeevi D., et al. 2015[22]	Other	800	not re-ported	Zeevi D., et al. 2015[22]	Other	100	not re-ported
					Mendes-Soares H., et al. 2019[S2]	North America	327	Oct 2016 to Dec 2017
Wang P., et al. 2019[28]	Wang P., et al. 2018[S9]	Asia	1290	Jan to Feb 2018	Wang P., et al. 2018[S9]	Asia	1138	Jan to Feb 2018
					Zhou G., et al. 2020[S10]	Asia	210	Jul 2015 to Jan 2019
					Wang P., et al. 2020[S11]	Asia	367	Jun to Sep 2019
					Becq A., et al. 2020[S12]	Not re-ported	50	Not re-ported
Wu L., et al. 2019[29]	Wu L., et al. 2019[29]	Asia	>3000	Aug 2018 to Oct 2018	-	-	-	-
Oka R., et al. 2019[30]	-	-	-	-	-	-	-	-
Lin H., et al. 2019[31]	Long E., et al. 2017[S13]	Asia	886	Not re-ported	Long E., et al. 2017[S13]	Asia	57	Jan 2012 to Mar 2016
Wang P., et al. 2020[32]	Wang P., et al. 2018[S9]	Asia	1290	Jan to Feb 2018	Wang P., et al. 2018[S9]	Asia	1138	Jan to Feb 2018
					Zhou G., et al. 2020[S10]	Asia	210	Jul 2015 to Jan 2019
					Wang P., et al. 2020[S11]	Asia	367	Jun to Sep 2019
					Becq A., et al. 2020[S12]	Not re-ported	50	Not re-ported
Chen D., et al. 2020[33]	Wu L., et al. 2019[29]	Asia	>3000	Aug 2018 to Oct 2018	-	-	-	-
Gong D., et al. 2020[34]	Gong D., et al. 2020[34]	Asia	>5000	Not re-ported	-	-	-	-

Wijnberge M., et al. 2020[36]	Hatib F., et al. 2018[S14]	North America	1334	2005 to 2014	Hatib F., et al. 2018[S14]	North America	204	Dec 2015 to Jan 2017
					Davies S., et al.[S15]	Europe	255	Nov 2016 to Dec 2017
Maheshwari K., et al. 2020[39]	Hatib F., et al. 2018[S14]	North America	1334	2005 to 2014	Hatib F., et al. 2018[S14]	North America	204	Dec 2015 to Jan 2017
					Davies S., et al.[S15]	Europe	255	Nov 2016 to Dec 2017
Schneck E., et al. 2020[37]	Hatib F., et al. 2018[S14]	North America	1334	2005 to 2014	Hatib F., et al. 2018[S14]	North America	204	Dec 2015 to Jan 2017
					Davies S., et al.[S15]	Europe	255	Nov 2016 to Dec 2017
Auloge P., et al. 2020[40]	-	-	-	-	-	-	-	-
Wong C., et al. 2020[41]	-	-	-	-	-	-	-	-
Aguilera A., et al. 2020[42]	-	-	-	-	-	-	-	-
Hill N., et al. 2020[43]	Hill N., et al. 2019[S16]	Europe	2994837	Jan 2006 to Dec 2016	Sekelj S., et al. 2020[S17]	Europe	604135	Jan 2006 to Dec 2013
Yao X., et al. 2021[44,45]	Attia ZI., et al. 2019[S18]	North America	44959	Jan 1994 - Feb 2017	Attia ZI., et al. 2019[S19]	North America	6008	Sep 2018
					Adedinsewo D., et al. 2020[S20]	North America	1606	May 2018 to Feb 2019
					Attia ZI., et al. 2020[S21]	North America	27	Not re-ported

Supplementary references reported in Supplementary Table 4:
S1. El-Solh., et al. Predicting effective continuous positive airway pressure in sleep apnea using an artificial neural network. Sleep Med. 2007. [PMID: 17512788]
S2. Mendes-Soares H., et al. Assessment of a Personalized Approach to Predicting Postprandial Glycemic Responses to Food Among Individuals Without Diabetes. JAMA Netw. Open. 2019. [PMID: 30735238]
S3. Faro J., et al. Comparison of a Collective Intelligence Tailored Messaging System on Smoking Cessation Between African American and White People Who Smoke: Quasi-Experimental Design. JMIR Mhealth Uhealth. 2020. [PMID: 32338619]
S4. Calvert JS., et al. A computational approach to early sepsis detection. Comput Biol Med. 2016. [PMID: 27208704]
S5. McCoy A., et al. Reducing patient mortality, length of stay and readmissions through machine learning-based sepsis prediction in the emergency department, intensive care unit and hospital floor units. BMJ Open Qual. 2017. [PMID: 29450295]
S6. Mao Q., et al. Multicentre validation of a sepsis prediction algorithm using only vital sign data in the emergency department, general ward and ICU. BMJ Open. 2018. [PMID: 29374661]
S7. Stephens T., et al. Feasibility of pediatric obesity and prediabetes treatment support through Tess, the AI behavioral coaching chatbot. Transl Behav Med. 2019. [PMID: 31094445]
S8. Green E., et al. Expanding Access to Perinatal Depression Treatment in Kenya Through Automated Psychological Support: Development and Usability Study. JMIR Form Res. 2020. [PMID: 33016883]
S9. Wang P., et al. Development and validation of a deep-learning algorithm for the detection of polyps during colonoscopy. Nat Biomed Eng. 2018. [PMID: 31015647]
S10. Zhou G., et al. Computer aided detection for laterally spreading tumors and sessile serrated adenomas during colonoscopy. PLoS One. 2020. [PMID: 32315365]
S11. Wang P., et al. Lower Adenoma Miss Rate of Computer-Aided Detection-Assisted Colonoscopy vs Routine White-Light Colonoscopy in a Prospective Tandem Study. Gastroenterology. 2020. [PMID: 32562721]
S12. Becg A., et al. Effectiveness of a Deep-learning Polyp Detection System in Prospectively Collected Colonoscopy Videos With Variable Bowel Preparation Quality. J Clin Gastroenterol. 2020. [PMID: 31789758]
S13. Long E., et al. An artificial intelligence platform for the multihospital collaborative management of congenital cataracts. Nature Biomedical Engineering. 2017. [doi.org/10.1038/s41551-016-0024]
S14. Hatib F., et al. Machine-learning Algorithm to Predict Hypotension Based on High-fidelity Arterial Pressure Waveform Analysis. Anesthesiology. 2018. [PMID: 29894315]
S15. Davies S., et al. Ability of an Arterial Waveform Analysis-Derived Hypotension Prediction Index to Predict Future Hypotensive Events in Surgical Patients. Anesth Analg. 2020. [PMID: 30896602]
S16. Hill NR., et al. Predicting atrial fibrillation in primary care using machine learning. PLoS One. 2019. [PMID: 31675367]
S17. Sekelj S., et al. Detecting undiagnosed atrial fibrillation in UK primary care: Validation of a machine learning prediction algorithm in a retrospective cohort study. Eur J Prev Cardiol. 2020. [PMID: 32787456]
S18. Attia Z., et al. Screening for cardiac contractile dysfunction using an artificial intelligence-enabled electrocardiogram. Nat Med. 2019. [PMID: 30617318]
S19. Attia Z., et al. Prospective validation of a deep learning electrocardiogram algorithm for the detection of left ventricular systolic dysfunction. J Cardiovasc Electrophysiol. 2019. [PMID: 30821035]
S20. Adedinsewo D., et al. Artificial Intelligence-Enabled ECG Algorithm to Identify Patients With Left Ventricular Systolic Dysfunction Presenting to the Emergency Department With Dyspnea. Circ Arrhythm Electrophysiol. 2020. [PMID: 32986471]
S21. Attia Z., et al. Artificial Intelligence ECG to Detect Left Ventricular Dysfunction in COVID-19: A Case Series. Mayo Clin Proc. 2020. [PMID: 33153634]