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Unleashing the potential of AI: a deeper dive into GPT prompts for medical research

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I read the article by Haemmerli *et al* on the performance of ChatGPT-3.5 in generating treatment recommendations for central nervous system (CNS) tumours, which were then evaluated by tumour board (TB) experts. While the study did illuminate promising aspects of the Artificial Intelligence (AI) model, the design of the prompt used to interact with ChatGPT warrants further consideration.

In the study, the prompt employed was a brief patient history, followed by two questions, which appears to have limited the model's performance. As a sophisticated large language model (LLM), GPT-3.5 relies heavily on the context and specificity of the provided prompt.[1 2] Based on cited literature, an alternative prompt structure could have included context, specific intent, a question and an expected response format. Moreover, pretraining the LLM with examples of the expected answer significantly improves the quality of the answer.[2 3] Finally, the introduction of GPT-4 in early March 2023 has shown considerable improvement in understanding and generating responses when compared with ChatGPT-3.5.[4 5]

Table 1 ChatGPT-3.5 from the paper's online supplemental material S1 (6), chaptGPT-3.5 and GPT-4 adapted output

ChatGPT-3.5 with simple prompt (from the study[6])	ChatGPT-3.5 with pretraining and structured prompt	GPT-4 with pretraining and structured prompt
Patient 9		
'(…)the patient has a malignant brain tumour known as an astrocytoma. These tumours are typically treated with a combination of surgery, radiation therapy and chemotherapy.(…)'	'Oncological diagnosis: Glioblastoma (WHO grade IV) right precentral lesion(…) Proposed treatment: Palliative care, supportive management. Discussion: Considering the patient's age, comorbidities and postoperative complications, the panel recommends a palliative approach.(…)'	'Oncological diagnosis: Glioblastoma (WHO grade IV) Right precentral Lobe(…) Proposed treatment: Due to the poor general condition and advanced age of the patient,(…)focus should be on symptomatic relief, quality of life, and palliative care. Discussion: (…)The tumour board suggests a supportive and palliative care approach(…). Regular follow-ups with palliative care and neurology teams should be established(…).'
Patient 10		
'(…)the patient likely has a grade III or IV astrocytoma. The best adjuvant treatment for this type of tumour would likely be a combination of radiation therapy and chemotherapy with temozolomide It is also important to note that the patient has IDH-1 wild type, which is associated with poor outcome and less response to chemotherapy and radiation therapy.'	'Oncological diagnosis: Glioblastoma (WHO grade IV) left frontotemporal lesion Proposed treatment: Radiotherapy and chemotherapy. Discussion: In the case of a gross total resection of a left frontotemporal glioblastoma, the neurotumour board recommends adjuvant treatment with radiotherapy and chemotherapy. (…)Close monitoring and follow-up will be essential to assess treatment response(…)'	'Oncological diagnosis: Glioblastoma (WHO grade IV) left frontotemporal lobe proposed treatment: (…)Standard adjuvant radiotherapy and chemotherapy using temozolomide according to the STUPP protocol.(…) Discussion: (…)an unmethylated MGMT promoter suggests a less favourable response to temozolomide chemotherapy, however, given the patient's overall good health status, adjuvant radiochemotherapy remains the standard of care.(…)'

MGMT, O6-methylguanine-DNA methyltransferase; IDH-1, isocitrate dehydrogenase 1; STUPP protocol, temozolomide + radiotherapy according to Roger Stupp's regimen

With the application of these techniques, researchers could have guided the predictive capabilities of the LLM to generate more relevant and contextually nuanced responses. This could have particularly helped in areas where the model underperformed, such as precision in glioma subtypes and considerations of patient functional status.

As an illustration, both ChatGPT-3.5 and GPT-4 were pretrained with eight examples (patients 1–8, patient history followed by TB response) from online supplemental material of the study. A more context-specific prompt was then used with the history of patients 9 and 10. Table 1 displays main output obtained using this technique, revealing enhanced precision in oncological diagnosis, treatment discussions and patient functional status from ChatGPT-3.5 compared with what was presented in the paper. GPT-4 seemed to align even more closely with the board's opinion, which was defined as the gold standard. Full discussion with the chatbot is available in online supplemental material 1.

It is critical to acknowledge that the efficiency of LLMs applications heavily depends on the prompt used and the quality of the data given. Future research needs to employ a refined, context-driven approach in interacting with these models and the development and sharing of prompt engineering techniques should continue to be prioritised.

In conclusion, the exploration of LLM in CNS oncology research is commendable, but it is essential to optimise the methodology to fully unlock the true potential of AI tools in such a complex and challenging clinical landscape.

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Road map for clinicians to develop and evaluate AI predictive models to inform clinical decision-making

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ABSTRACT

Background Predictive models have been used in clinical care for decades. They can determine the risk of a patient developing a particular condition or complication and inform the shared decision-making process. Developing artificial intelligence (AI) predictive models for use in clinical practice is challenging; even if they have good predictive performance, this does not guarantee that they will be used or enhance decision-making. We describe nine stages of developing and evaluating a predictive AI model, recognising the challenges that clinicians might face at each stage and providing practical tips to help manage them.

Findings The nine stages included clarifying the clinical question or outcome(s) of interest (output), identifying appropriate predictors (features selection), choosing relevant datasets, developing the AI predictive model, validating and testing the developed model, presenting and interpreting the model prediction(s), licensing and maintaining the AI predictive model and evaluating the impact of the AI predictive model. The introduction of an AI prediction model into clinical practice usually consists of multiple interacting components, including the accuracy of the model predictions, physician and patient understanding and use of these probabilities, expected effectiveness of subsequent actions or interventions and adherence to these. Much of the difference in whether benefits are realised relates to whether the predictions are given to clinicians in a timely way that enables them to take an appropriate action.

Conclusion The downstream effects on processes and outcomes of AI prediction models vary widely, and it is essential to evaluate the use in clinical practice using an appropriate study design.

INTRODUCTION

Healthcare systems worldwide generate enormous amounts of patient-related health data, much of which is electronic in developed countries. There is growing interest among clinicians and healthcare staff in how they could use these data to support patient care.[1] Much of medicine is about anticipating and reducing risk, based on current and historical experiences. Predictive analytics in healthcare can help determine the risk of a patient developing a particular condition or complication, which can inform the shared decision-making process between clinicians and patients and improve patient satisfaction with their overall medical care.[2–7] With the new era of artificial intelligence (AI), clinical prediction tools can help personalise treatment and management decisions.

The Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD) framework was published to guide developing multivariate predictive models,[8] outlining what should be reported (eg, data sources, modelling techniques) when written up for publication.[9] However, a recent systematic review highlighted how these models' reporting has been rather poor since its publication.[10] TRIPOD also only focused on regression-based prediction models (although it can be applied to AI-generated approaches) and highlighted the need for more 'practical methods' for developing models more commonly used in healthcare (ie, supervised learning techniques).[11] The Consolidated Standards of Reporting Trials–AI guidelines were published in 2020 to help readers conceive studies with AI interventions; however, there was limited guidance on how these AI predictive models could be developed and usefully applied in clinical practice[12]; clinicians have sought further information on this.[1 13] Even if a newly developed AI model has a good predictive performance, this does not guarantee that it will be used in clinical practice or enhance clinical decision-making, let alone improve health outcomes.[14] The quality criteria important for evaluating AI predictive models were described in a recent scoping review; however, little information was provided on how such tools affect the clinical routine of physicians, which may vary per physician.[15]

The nine stages for developing and evaluating predictive AI models

Stage 1: clarifying the clinical question or outcome(s) of interest (output).

Stage 2: identifying appropriate predictors (features selection).

Stage 3: choosing relevant datasets.

Stage 4: developing the AI predictive model.

Stage 5: validating and testing the developed model.

Stage 5: presenting and interpreting the model prediction(s).

Stage 7: licensing the AI predictive model.

Stage 8: maintaining the AI predictive model.

Stage 9: ongoing evaluation of the impact of the AI predictive model.

It is vital to seek the input of a multidisciplinary team early when developing AI predictive models. This includes clinical specialists when deciding how the model could potentially enhance clinical decision-making and computing scientists when selecting the most appropriate algorithm(s).[16] Patients and providers should also be involved in deciding if the recommendations will be presented to them, including what, how and when information might be usefully presented (ie, content and alerts).[2 7 17] Taking each of these stages in turn.

STAGE 1: CLARIFYING THE CLINICAL QUESTION OR OUTCOME(S) OF INTEREST (OUTPUT)

The clinical question or outcome(s) of interest should be clearly defined from the onset. An example of a clinical question might be 'what is the likelihood of a patient developing type 2 diabetes mellitus (T2DM)?' to modify some of the patient's potential risk factors through lifestyle changes and/or prescribing medication.[18] It is essential to consider how we define T2DM here. Kopitar *et al* defined it as a fasting plasma glucose level of 6.1 mmol/L or higher without diabetes symptoms.[18] This definition makes the model a prognostic rather than diagnostic predictive model, given that it focuses on predicting a future health outcome. It is worth mentioning that this definition varies from those presented in different clinical guidelines[18] and can also change over time, highlighting the importance of model upgrading and maintenance. Another example of a clinical question could be 'what is the likelihood of a patient developing an infection and subsequent sepsis as an inpatient?'. Again, multiple definitions of sepsis could be used,[19–21] each varying in how closely aligned it is with the systemic effects of sepsis syndrome (see figure 1).[19 20] However, the choice of definition here is critical as it can directly influence the model performance measures, particularly specificity, which we will discuss later.[22] Clinicians should decide on the most accurate clinical definition for the predicted output, with the model upgraded to reflect any future changes to this definition.

STAGE 2: IDENTIFYING APPROPRIATE PREDICTORS (FEATURE SELECTION)

The second step involves identifying appropriate clinical predictors (features) related to the outcome of interest. Thus, if we take our sepsis-3 definition (figure 1), the next question relates to 'what clinical variables should we use for predicting sepsis?'. These clinical predictors will again depend on whether you want to develop a prognostic predictive model (which predicts the likelihood of sepsis occurring before the systemic inflammation process begins)[23] or a diagnostic predictive model (which early detects the likelihood of sepsis but after the inflammation process has already begun).[24] A review of the medical literature can help identify potential predictors that might be worth considering; 194 clinical predictors have been previously used to train machine learning algorithms for sepsis prediction, 13 of which were used across all 17 newly developed algorithms.[22] These 13 predictors contained a blend of non-modifiable (eg, age, gender) and modifiable (eg, blood glucose levels, blood pressure) predictors, the latter potentially increasing the applicability of the model in clinical practice.[22] It is important to consider here how these predictors have been defined and selected in previous studies, their source (ie, retrospective or real-time data) and whether any were excluded, thus recognising any inherent bias.[14 25] In terms of predictor type, numerical predictors should be given preference over categorical predictors, whenever possible.[8 26–28] A classic example is blood pressure, which can be recorded as a numerical (eg, 110 mm Hg) or categorical (eg, high,

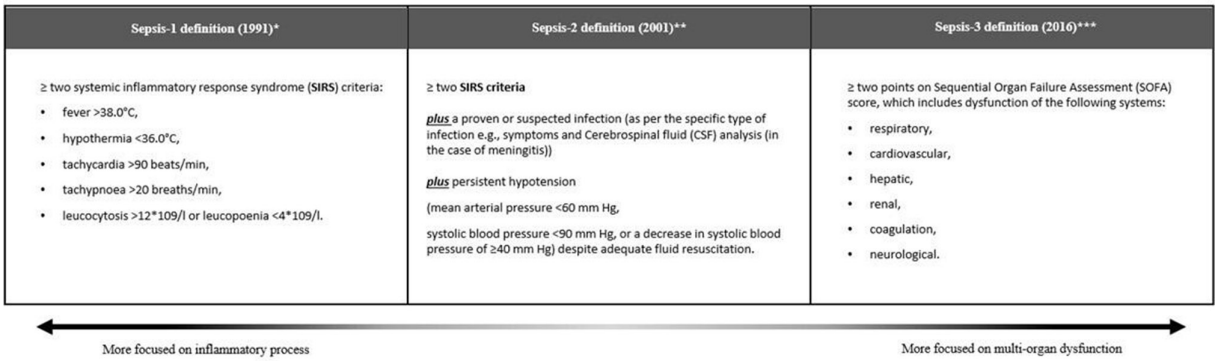

Figure 1 Different definitions of sepsis and their related clinical predictors. *Note that SIRS criteria are non-specific on the type of infection. **Note that suspected infection became a requirement to define sepsis. ***Note that clinical parameters are more specific to the systemic mechanism of sepsis.

normal, low) value. The latter assumes that a patient with systolic blood pressure of 110 mm Hg has the same level of hypotension as another patient with systolic blood pressure below 90 mm Hg, which is more characteristic of sepsis. In the T2DM example mentioned above, Kopitar *et al* screened the electronic health records (EHRs) of patients who went on to develop T2DM to identify potentially modifiable (eg, total cholesterol) and non-modifiable (eg, age) predictors.[18] EHR data can also allow exploring variables with predictive potentials that might not have been considered.[18]

The potential clinical predictors are then correlated to the model's outcome of interest (output) using either statistical methods or machine learning techniques.[29] Some predictors are likely to correlate strongly to the output but may be more suitable for a diagnostic rather than a prognostic predictive model. For example, the Sequential Oragn Failure Assessment Score (SOFA) Score, which reflects multiorgan dysfunction, will have a strong correlation with the sepsis diagnosis and would be more suitable for developing a diagnostic predictive model, whereas lipid profile will have a strong correlation to the diabetes prognosis and would be more suitable for developing a prognostic predictive model; this is because patients with established diabetes are likely to have hypercholesterolaemia.[18] We suggested using a 'blended approach' for predictor selection, where the predictors are correlated to the model's output and clinical input is also obtained on the choice to support its clinical application.[19 22 30]

STAGE 3: CHOOSING RELEVANT DATASETS

The existence, choice and access to relevant datasets often represent a limiting step for developing predictive AI models.[1 31] Thousands of organisations hold health datasets in the UK, so it can be difficult for clinicians, researchers and innovators to discover what datasets already exist.[32–34] Developers should first look at the relevance, data size and diversity of potential datasets; the proposed dataset should ideally represent the targeted population where the AI model is intended to be used to reduce the risk of inherent bias.[35] If the key outcome(s) of interest is unidentified, developers may have to decide how these available variables are used to define the key outcome. Researchers and innovators can search and request access to UK health-related datasets through 'the Gateway', a common entry point established by the Health Research Authority for nine UK-based health data research (HDR) hubs across the country.[33] These hubs include DATAMIND (mental health data), PIONEER (acute care data) and Discover-Now (primary care data), the latter being one of the largest primary care datasets in Europe. The UK HDR Alliance is also an independent alliance of leading healthcare and research organisations united to establish best practices for the ethical use of UK health data for research at scale.[34] In the UK, patients' information is protected by the General Data Protection Regulation and patients can refuse to permit their confidential data to be used through the national data opt-out service. Deidentification can be challenging, specifically with demographic variables, some of which can be important predictors when training the model. Removing them can potentially risk the efficiency of the model performance. A trusted research environment with anonymised patient data can be prepared for the clinician or researcher, once all the necessary ethical approvals have been obtained and the required training on data use and security completed.[36–39] Alternatively, data can be processed in a safe environment either at a hospital or university site; however, checks will need to be made on the safety of these environments and these data not approved for release if they do not meet the HDR UK five safes (safe people, safe projects, safe settings, safe outputs and safe data).[34] The diabetes risk prediction model mentioned above was developed using anonymised data collected from 10 diabetes screening clinics pooled in a single database.[18] Internationally, the Medical Information Mart for Intensive Care (MIMIC) database has clinical information from more than 40 000 patients admitted to critical care units at one tertiary centre (Beth Israel Deaconess Medical Centre, Boston, Massachusetts, USA). Similarly, healthcare professionals can freely access the dataset after completing appropriate data use and security training and signing a data usage agreement.[36 40] An important consideration is how these data have been collected and recorded. Numerical variables in the chosen dataset should ideally be collected and recorded synchronously.[37] The MIMIC database developers recognised this as a potential limitation of their dataset, with vital signs like heart rate and blood pressure recorded at different time points, thus potentially impacting the accuracy of the model.[36] Clinicians should help decide which dataset best represents the patient population that this model is intended to be used in.

STAGE 4: DEVELOPING THE AI PREDICTIVE MODEL

There are four major types of machine learning algorithms: supervised learning, unsupervised learning, semisupervised learning and reinforcement learning.[41] The choice of machine learning algorithm will depend on some factors, including the outcome of interest (ie, numerical or discrete value); the number of predictors; the 'shape' of the dataset (ie, size, completeness, uniformity); and the performance measures of the algorithm (ie, sensitivity, specificity, accuracy, area under the curve).[30] In the case of the latter, a number of algorithms may need to be tried first before finally deciding on the most suitable one or combination (ensemble model).[41] Supervised learning is commonly used for predictive models and can be subclassified into regression (ie, numerical output) or classification (ie, discrete output) algorithms.[42] The higher the number of predictors used, the more computational power needed to train the model and the higher the potential risk of overfitting.[42] An overfitting model is

a model that has high accuracy during the training phase, but lower accuracy during the validation and testing phase; potential ways to overcome this are described below.[26 42 43] It is important to remember, however, that strong computational correlations primarily depend on the entry values (eg, non-extreme vs extreme) and amount of missing data. Missing data can be potentially managed by statistical methods (ie, multiple imputations) or machine learning algorithms (ie, K-nearest neighbours), the choice of which will usually depend on the type and extent of missing information.[41 44 45]

Deep learning and artificial neural networks can perform better than conventional machine learning techniques. These networks act as a net of neurons that can identify patterns and correlations in a dataset so the model can self-learn from these patterns. The 'deep' refers to the depth of layers in a neural network and the performance measures of a deep learning model are directly correlated to the data size (ie, the larger the dataset, the better the model performance).[46 47] However, this can be challenging with rare diseases.[42 46 48]

Python is one of the most common programming languages for developing AI predictive models and is freely available.[49] After importing the dataset into programming software, you usually divide it into two portions: training the algorithm (70%) and internal validation (30%).[41 43] As described in stage 2 above, each predictor is then correlated to the outcome of interest (feature selection) using the training set and the performance measures of the algorithm calculated. This includes the specificity, sensitivity, receiver operating characteristic (ROC) curve and the area under the ROC curve (AUROC curve). The AUROC curve measures the distinctive ability of the algorithm to predict the outcome, with a value of >0.9 considered excellent.[22 50] AI systems learn to make decisions based on these training data, which may reflect human biases or social inequities, even if predictors such as race or gender have been removed.[51] It is beneficial to have the input of a programming specialist when preparing/revising the codes and judging the performance measures of any resulting models.

STAGE 5: VALIDATING AND TESTING THE AI PREDICTIVE MODEL

After developing the model, its predictive accuracy is reassessed using a validation dataset (internal validation) and again in a completely new, unseen dataset (ie, externally validated), ideally from another site. This comparison of performance measures is important for evaluating the risk of over/underfitting and widening the generalisability of the model, considering the diversity and representation of the patient population.[52] The testing phase usually involves running the model in a silent clinical environment, where the output is not shared with clinicians but compared with conventional clinical judgement and diagnosis. The T2DM prediction model was tested in a silent clinical environment over 6 months to assess its performance, before 'going live' to support clinical decision-making.[18] It is important to recognise that not all data are equal in quality; laboratory values may be coded differently or missing for some or all of an entire predictor in validation and training datasets. Complete case analysis is a method that can handle missing data and involves removing all missing patient cases; however, this requires a large sample size and may introduce selection bias. Alternatively, mean imputation can be used for missing numerical predictors, but can be sensitive to outliers (ie, extreme values).[53]

STAGE 6: PRESENTING AND INTERPRETING THE MODEL PREDICTION(S)

It is essential to consider how the model prediction(s) is presented to target users (patients/clinicians) and whether a recommendation accompanies it. The predicted probability (output) can be presented to users without any corresponding recommendations; this assistive presentation format allows clinicians to combine these predictions with clinical judgement.[54 55] In contrast, a directive prediction model provides the physician with a recommendation in addition to the predicted probability; this, in turn, can potentially increase the ease of use of the AI prediction model, especially if integrated into the electronic ordering system.[56 57] Clinicians should be informed of the underlying assumptions of the model, including which predictors were included and why, any inherent bias (eg, if groups are over-represented or under-represented in the training data) and how patients with specific outcome risk profiles might be affected by different recommendations.[14] For example, the inclusion of health costs as a proxy for health needs could potentially introduce racial bias, as less money is spent on black patients who have the same level of need in the USA; in other words, the algorithm could falsely conclude that black patients are healthier than equally sick white patients.[58] There is some evidence that clinicians in English-speaking countries have felt more legally supported when using decision support tools because they can provide documented evidence for the rationale behind their decisions.[59] Chua *et al* proposed an AI–human interface, where clinicians identify which patients might be eligible to use the tool, and the algorithm identifies (more accurately) which patients have serious illness communication needs and promotes upstream data collection.[7] Target users should contribute to the design of the model interface, ensuring that it is user-friendly, and any outputs and recommendations are easy to understand.

STAGE 7: LICENSING THE AI PREDICTIVE MODEL

In the UK, AI-based tools are classified as medical devices and therefore need the Medicines and Healthcare products Regulatory Agency (MHRA) approval. Before Brexit, approved tools required either the 'United Kingdom Conformity Assessed' (UKCA) or 'Conformité Européenne' logo to be marketed in Europe.[60] However,

from July 2023, only tools with the UKCA logo will be allowed to be marketed in the UK.[61] In Europe, AI-based software and tools are regulated by the EU Medical Device Regulation (EU MDR),[31 62 63] whereas in the USA, AI-based tools are regulated by the Food and Drug Administration.[64]

To licence an AI predictive tool in the UK, the MHRA must ensure that it complies with certain 'conformity assessment' standards, described by the National Institute for Health and Care Excellence (NICE) in 2018 and updated in 2021.[65] It is worth mentioning that NICE framework is designed for AI tools with fixed algorithms (ie, no change over time) rather than AI tools with adaptive algorithms (ie, continually and automatically change)[65]; the latter are covered by separate standards (including principle 7 of the code of conduct for data-driven health and care technology).[65] Higher-risk AI tools are classified as those that either target vulnerable patient populations, have serious consequences with errors or system failure, are used solely by patients without healthcare professionals' support or require a change in clinical workflow.[65] For EU-approved tools, the tool should comply with the general safety and performance requirements stated by the EU MDR.[66 67] Clinicians should be aware of the appropriate approvals that need to be obtained, especially with the growing adoption of these tools.

STAGE 8: MAINTAINING THE AI PREDICTIVE MODEL

Maintenance of the model and knowledge management are critical.[68] It may be necessary to update the model as populations, diseases and treatments change and include an expiry date.[68] In the UK, NICE data framework recommends a regression test be done when the model is updated to ensure that any new changes do not have a negative impact on its performance, reliability and functionality.[65] Model developers should also keep users (clinicians and patients) informed when releasing new model versions. In the USA, model recertification is needed when AI predictive models are updated,[15] although the US FDA is currently working on a framework that allows repeated updating of an AI predictive model without recertification through a change control plan.[69]

STAGE 9: ONGOING EVALUATION OF THE IMPACT OF THE AI PREDICTIVE MODEL

Introducing an AI prediction model into clinical practice can be considered a complex intervention; it usually consists of multiple interacting components including the accuracy of the model predictions, physician and patient understanding and use of these probabilities, expected effectiveness of subsequent actions or interventions, and adherence to these. A new framework has now replaced the UK Medical Research Council's guidance for developing and evaluating complex interventions. It focuses on recent developments in methods and the need to optimise the efficiency, use and impact of research.[70]

The downstream effects on patient outcomes of using an AI prediction model are not always predictable. For example, Kappen *et al* described no decrease in the incidence of postoperative nausea and vomiting, despite an increase in the administration of prophylactic antiemetics in the cluster-randomised trial of the AI prediction model (using an assistive presentation format).[56] This may indicate that either the predictive performance of the model was insufficient, the impact on physician decision-making was too small (eg, too few prophylactic drugs were administered despite high predicted probabilities), the antiemetic drugs were not as effective as thought, and/or patients chose not to take them.[56] Collecting additional data (observations and interviews) may help improve our understanding of these study results.

When designing an impact study before applying to licensing, a clinician needs to consider whether the complex intervention will have an individual effect on patients or whether it induces a more group-like effect.[56] A prediction model often aims to affect the clinical routine of a physician, which may vary per physician; this could lead to clustering of the effect per physician or practice (hospital) when the AI model use is compared across providers or practices.[19 31 56] After repeated exposure to the predictions, clinicians may also become better at estimating the probability in subsequent similar patients, even when those patients are in the control group.[19 31 56] This likely dilutes the effectiveness and thus impact of the model use.[48 56] As Kappen *et al* highlights, the effects of a learning curve may be minimised, though not completely prevented, by randomisation at a cluster level, for example, physicians or hospitals.[52 56]

CONCLUSION

We have provided a road map which clinicians and others developing algorithms can use to develop and evaluate AI predictive models to inform clinical decision-making. We described the nine stages, recognising the challenges that clinicians might face at each stage and practical tips to manage them. A 'blended approach' should be considered for clinical predictor selection, and the proposed dataset clearly represents the targeted population where the AI model is intended to be used. Comparing performance measures between the different training, validation and unseen clinical datasets are important for evaluating the risk of over/underfitting and widening the generalisability of the model. The format of the predictive model (assistive or directive) should be carefully chosen and designed. The maintenance of the model is important as populations, diseases and treatments change. The downstream effects on patient outcomes of using an AI prediction model are not always predictable, and it is important to evaluate its use in clinical practice using an appropriate study design.

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Assessing the efficient use of the lightwave health information management system for health service delivery in Ghana

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ABSTRACT

Background In achieving the WHO's Universal Health Coverage and the Global Developmental Agenda: Sustainable Development Goal 3 and 9, the Ministry of Health launched a nationwide deployment of the lightwave health information management system (LHIMS) in the Central Region to facilitate health service delivery. This paper assessed the efficient use of the LHIMS among health professionals in the Central Region.

Methods A non-interventional descriptive cross-sectional study design was employed for this research. The study used stratified and simple random sampling for selecting 1126 study respondents from 10 health facilities that use the LHIMS. The respondents included prescribers, nurses, midwives and auxiliary staff. Descriptive statistics (weighted mean) was computed to determine the average weighted score for all the indicators under efficiency. Also, bivariate (χ^2) and multivariate (ordinal logistic regression) analyses were conducted to test the study's hypotheses.

Results Findings revealed that the LHIMS enhanced efficient health service delivery. From the bivariate analysis, external factors; sex, educational qualification, work experience, profession type and computer literacy were associated with the efficient use of the LHIMS. However, training offered prior to the use of the LHIMS, and the duration of training had no association. At the multivariate level, only work experience and computer literacy significantly influenced the efficient use of the LHIMS.

Conclusion The implementation of LHIMS has the potential to significantly improve health service delivery. General computing skills should be offered to system users by the Ministry of Health to improve literacy in the use of computers. Active participation in the use of LHIMS by all relevant healthcare professionals should be encouraged.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ The WHO considers health information systems to be one of the six essential building blocks of any health system because they provide reliable information to aid in decision-making throughout the health system. Despite the benefits of electronic health records (EHRs), there are lower adoption and utilisation rates in lower-middle and low-income countries.

WHAT THIS STUDY ADDS

⇒ A non-interventional descriptive cross-sectional study design was employed for this research. It was revealed that sex, educational qualification and training prior to the use of lightwave health information management system (LHIMS) were not statistically significant to health professionals' use of the LHIMS-EHR. However, their years of work experience and computer efficacy have a significant effect on the efficient use of the system.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ In terms of the educational qualification of health professionals and the effect it has on the usability of the LHIMS, policy-makers will need to ensure that the health professionals they engage at their facilities have the required educational qualifications to work and use the LHIMS at the facility. Also, in terms of computer efficacy, policy-makers need to ensure that the health professionals they engage at their facilities have some level of computing knowledge.

INTRODUCTION

The WHO considers health information systems to be one of the six essential building blocks of any health system because they provide reliable information to aid in decision-making throughout the health system.[1 2] Relatedly, the recent global development agenda also sees health information systems as one of the critical health delivery components that contribute to achieving goal 3 (good health and well-being) and goal 9 (industry, innovation and infrastructure) of the Sustainable Development Goals.[3–6]

In Africa, medical information recording has evolved over the years; from the period of cave recordings, where records were stored on tablets of stone to an age where the paper system was introduced.[7] Until the latter part of the 20th century, a paper-based record

management system was the primary method of storing health records and other documents.[8] Although it can be tailored to the needs of each hospital and healthcare provider without requiring any technical changes, the introduction of the electronic health record (EHR) system has made paper-based records less effective in healthcare delivery. The limitations associated with the use of the paper-based system now make the EHR system the appropriate option.[9–11]

Even though EHR systems have evolved into a viable option, there are major drawbacks to their implementation in Africa. For instance, there are lower adoption and utilisation rates in lower-middle and low-income countries.[12 13] The implemented EHR systems in Africa focus on only a few health conditions such as HIV care, home-based care, injury surveillance, tertiary care, and maternal and reproductive health.[14–17]

To improve healthcare quality and accelerate the health service delivery processes in Ghana, the Ministry of Health (MoH) published the Health Sector Information and Communication Technology (ICT) Policy and Strategy charts in 2005. It was guided by the Ghana ICT for Accelerated Development policy to increase the adoption of ICT in the health sector.[18] Due to this, some health facilities implemented an EMR system meant for solo practice. The health facilities that used the EMR systems have frequently changed systems due to challenges such as poor report generation, the inability of the system to mimic the daily transactions performed during service delivery (work domain saturation) and clinicians' inability to type on a keyboard while attending to patients. Even though the information generated by the EMR could be shared across departments within one health facility, it was not able to share patient information across multiple providers. As a result of the challenge, some facilities used the system together with paper records as they couldn't fully implement a paperless system.

Due to these challenges, the MoH developed a new policy document in 2009 to aid in the implementation of a national EHR system, a common platform to be used by all health professionals in health facilities across the country. This new implementation was expected to streamline admission, discharge and transfer processes, and be integrated into the claims management system of the National Health Insurance Scheme for billing.[19]

Lightwave health information management system (LHIMS) is a web-based software platform that is capable of transmitting health information for use by authorised health service providers and supporting administrative functions such as managing records, making clinical orders, inputting information, storing and retrieval to assist in decision-making during and after the time of care in Ghana.[20] It is a comprehensive system with several components including National Health Insurance Authority (NHIA) claims, patient records, administrator, antenatal care, laboratory management, alerts and communication, appointment and scheduling, and radiology. The implementation of LHIMS started in 2017 in the Central Region of Ghana. Adoption is still in the early stages, and it is only about 10% of healthcare facilities have adopted the use of LHIMS.

It has been theorised by Davis[21] in the Technology Acceptance Model that external factors such as age, gender, organisational factors, etc influence the perceived usefulness of EHR Systems. Also, Al-Rayes *et al*[22] hypothesised that physicians' use of the EHR system is significantly influenced by their age, work experience and medical specialty. This paper, therefore, assesses health professionals' capacity to use LHIMS-EHR efficiently for health service delivery in Ghana.

MATERIALS AND METHODS

Study design

A non-interventional descriptive cross-sectional study design was employed for this research. The population for the study was all the health professionals in the Central Region of Ghana. However, the accessible population was limited to only the health professionals practising at the facilities using the LHIMS for service delivery in the Central Region of Ghana. The reason for targeting this section of health professionals only is that they have been practising with the LHIMS for service delivery at their various health facilities and, it is assumed that these health professionals will have the requisite knowledge of the LHIMS and that they will be able to provide the resourceful knowledge the study seeks to unravel about the LHIMS. In the early stages of implementation, some facilities stopped using the LHIMS because they faced challenges and eventually stopped using it. Other health facilities changed to alternative EHRs.

Sampling technique

A sample size formula was used to estimate 1126 sample size for the survey. A stratified probability sampling approach was used.

Data analysis

Weights of 1, 2, 3, 4 and 5 were assigned to all the 5-point likert scale; strongly disagree (SD), disagree (D), neutral (N), agree (A) and strongly agree (SA), respectively. The weighted mean formula from Manyange and Abuga[23] was employed to compute the weighted average (WA) scores. The weighted mean formula[24] was employed to compute the WA scores. The formula is mathematically written as WA=wx/ w, where w represents the weights and x represents the values. After the computation, the WA scores were interpreted based on the following parameters; 1.0–1.79=SD; 1.80–2.59=D; 2.60–3.39=N; 3.40–4.19=A; 4.20–5.00=SA.

For the bivariate and multivariate analysis, principal component analysis was used as a dimension reduction technique to obtain a factor score for the dependent variable (efficiency). In IBM Statistical Package for the Social Sciences, the result was further examined using the orthogonal rotation approach (Varimax). The

Table 1 Descriptive statistical analysis of the efficient use of LHIMS by respondents

Statement	SD 1	D 2	N 3	A 4	SA 5	Weighted average	Interpretation
I can use the LHIMS without written instructions	47	135	247	574	123	3.52	Agree
Using the LHIMS helps me provide the appropriate service for the patient	52	169	267	501	137	3.45	Agree
It is easy to get the LHIMS to do what I want it to do	29	98	206	595	198	3.74	Agree
I can complete a task quickly using the LHIMS	28	76	227	584	211	3.78	Agree
Interaction with the LHIMS requires less mental effort	22	75	216	616	197	3.79	Agree
Learning to operate the LHIMS was easy for me	31	116	253	549	177	3.64	Agree
LHIMS requires fewer steps possible to accomplish a task	38	132	247	562	147	3.58	Agree
I am familiar with the items on the screen of the LHIMS	42	124	217	581	162	3.62	Agree
An increased time is required to enter patient information	37	137	213	561	178	3.63	Agree
LHIMS is simple to use	28	106	213	598	181	3.71	Agree
I can recover from mistakes quickly and easily when using the LHIMS	22	54	252	611	187	3.79	Agree
Using the LHIMS gives me more control to handle patient treatment/service on time	33	105	229	583	176	3.68	Agree
Using the LHIMS reduces the time spent by a client at the Unit	61	149	209	519	188	3.55	Agree

Source: Agyemang, 2021.
Weighted average=∑wx/∑w.
Interpretation: 1.0–1.79=SD; 1.80–2.59=D; 2.60–3.39=N; 3.40–4.19=A; 4.20–5.00=SA.
A, agree; D, disagree; LHIMS, lightwave health information management system; N, neutral; SA, strongly agree; SD, strongly disagree.

Kaiser-Meyer-Olkin measure of sampling adequacy was greater than 0.5 for all measured constructs. Bartlett's sphericity test was significant (p=0.05), and the construct's eigenvalue was greater than 1, accounting for more than 50% of the variance in every construct with individual item loads greater than 0.4.

The study further employed Brooke's (1986) System Usability Scale to categorise the dependent variables to make the factor score reflect a natural setting. Respondents with a factor score of less than 30% were categorised as 'low'" those with scores above 30% but not more than 70% were defined as 'moderate', and those with a score of more than 70% were classified as 'high'. This categorisation made it possible to run a χ^2 test for the bivariate analysis and ordinal logistic regression analysis for the multivariate using the proportion of odds (OR) to interpret the differences in the use of LHIMS.

RESULTS

Descriptive statistics of respondents' efficient use of LHIMS

The questions in the descriptive analysis were adapted from the Computer System Usability Questionnaire designed by International Business Machines (IBM) and the Isometric questionnaires.

Table 1 shows the descriptive statistical analysis of the efficient use of the LHIMS for health service delivery by respondents in the Central Region. In order to determine the average weighted score for all of the indicators under efficiency, a 5-point Likert scale ranging from SD, D, N, A and SA were assigned weights of 1, 2, 3, 4 and 5, respectively.

Bivariate analysis of sociodemographic characteristics and efficient use of LHIMS

In table 2, a χ^2 test of independence was performed to examine the relationship between respondents' sex, age, educational qualification and years of work experience and the efficient use of LHIMS.

Professional characteristics and efficient use of LHIMS

Kaipio *et al*[25] postulate that there are significant differences between nurses' and physicians' experiences of the usability of EHR systems. Consequently, in table 3, a χ^2 test of independence was conducted to examine the relationship between the respondents' professional type and the institution where the professional was trained (training institution) and the efficient use of LHIMS.

Training and computer efficacy and the efficient use of LHIMS

In table 4, a χ^2 test of independence was conducted to assess the association between respondents' training status prior to the use of the LHIMS, duration of the training and computer efficacy and the efficient use of LHIMS.

Multivariate analysis of the efficient use of LHIMS by respondents

In table 5, multivariate analysis was performed to assess the influence of sociodemographic characteristics of

Table 2 Bivariate (cross-tabulation) analysis of sociodemographic characteristics and efficient use of LHIMS by respondents

Variable	Efficiency			P value
	Inefficient	Moderately efficient	Highly efficient	
Sex	Freq. (%)	Freq. (%)	Freq. (%)	
Female	186 (26.9)	282 (40.8)	223 (32.3)	0.022
Male	148 (34.0)	172 (39.5)	115 (26.4)	
Age				
20–29	160 (30.0)	225 (42.20)	148 (27.80)	0.610
30–39	148 (29.20)	196 (38.70)	163 (32.10)	
≥40	26 (30.20)	33 (38.40)	27 (31.40)	
Educational qualification				
Certificate holder	43 (33.1)	51 (39.2)	36 (27.7)	0.004
Diploma/Higher National Diploma	125 (27.4)	166 (36.3)	166 (36.3)	
Degree	166 (30.8)	237 (44.0)	136 (25.2)	
Years of work experience				
≤1 year	120 (32.8)	148 (40.4)	98 (26.8)	0.040
2–5 years	157 (30.0)	215 (41.1)	151 (28.9)	
≥6 years	57 (24.1)	91 (38.4)	89 (37.6)	

Source: Agyemang, 2021.
LHIMS, lightwave health information management system.

respondents (age, sex, educational qualification and years of work experience), professional characteristics (professional type, place of training and institution of training) and training/computer efficacy (training status, duration of training and computer efficacy) on the efficient use of the LHIMS. In model 1, ordinal logistic regression analysis was fitted to assess the relationship between respondents' sociodemographic characteristics (age, sex, educational qualification and years of work experience) on the efficient use of the LHIMS. In model 2, controlling for sex, educational qualification and years of work experience of respondents, ordinal logistic regression was fitted to assess professionals' characteristics (professional type and training institution the respondent attended). In model 3, accounting for sex, educational qualification, work experience and training of professionals prior to EHR use, ordinal logistic regression was fitted to assess computer efficacy and the efficient use of the LHIMS.

DISCUSSION

According to the MoH,[26] it is becoming increasingly evident that many developing countries, including Ghana, would struggle to meet all the global targets required to improve their health sector. As a result, a national e-health system, the LHIMS, was necessary for the health sector to improve service efficiency and function as the country's EHR and a biosurveillance system.[26]

Table 3 Bivariate (cross-tabulation) analysis of professional characteristics and efficient use of LHIMS by respondents

Variable	Efficiency			P value
	Inefficient	Moderately efficient	Highly efficient	
Professional type	Freq. (%)	Freq. (%)	Freq. (%)	
Prescribers	86 (34.0)	116 (45.8)	51 (20.2)	0.003
Nurses and midwives	212 (29.0)	281 (38.4)	239 (32.7)	
Auxiliary	36 (25.5)	57 (40.4)	48 (34.0)	
Training institution				
MOH training institution (NMTC, CoH, community)	187 (29.7)	261 (41.5)	181 (28.8)	0.543
University	147 (29.6)	193 (38.8)	157 (31.6)	

Source: Agyemang, 2021.
LHIMS, lightwave health information management system; MoH, Ministry of Health.

Table 4 Bivariate (cross-tabulation) analysis of training/computer efficacy and LHIMS efficiency for health service delivery by respondents

	Efficiency			
Variable	**Inefficient**	**Moderately efficient**	**Highly efficient**	**P value**
Training	**Freq. (%)**	**Freq. (%)**	**Freq. (%)**	
Yes	303 (30.2)	414 (41.2)	287 (28.6)	0.011
No	31 (25.4)	40 (32.8)	51 (41.8)	
Duration of training				
Never trained	34 (27.9)	55 (45.1)	33 (27.0)	0.263
1–2 days	178 (28.6)	248 (39.9)	196 (31.5)	
3–4 days	66 (36.9)	62 (34.6)	51 (28.5)	
5 days or more	56 (27.6)	89 (43.8)	58 (28.6)	
Computer efficacy				
Beginners	83 (34.6)	112 (46.7)	45 (18.8)	0.000
Advanced users	251 (28.3)	342 (38.6)	293 (33.1)	

Source: Agyemang, 2021.
LHIMS, lightwave health information management system.

Table 5 Ordinal logistic regression analysis of sociodemographics, professional characteristics and training/skill on the efficient use of LHIMS by respondents

	Model 1	Model 2	Model 3
Variable	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**
Sociodemographic			
Sex			
Female	1.286 (1.021 to 1.62)*	1.276 (1.013 to 1.609)*	1.199 (0.947 to 1.518)
Male	1.00	1.00	1.00
Educational qualification			
Certificate	0.96 (0.67 to 1.374)	0.92 (0.641 to 1.321)	0.879 (0.611 to 1.265)
Diploma/Higher National Diploma (HND)	1.336 (1.052 to 1.698)*	1.288 (1.01 to 1.641)*	1.245 (0.976 to 1.589)
Degree+	1.00	1.00	1.00
Work experience			
≤1 year	0.621 (0.458 to 0.842)*	0.622 (0.458 to 0.844)*	0.628 (0.462 to 0.852)*
2–5 years	0.714 (0.537 to 0.95)*	0.721 (0.541 to 0.96)*	0.724 (0.544 to 0.965)*
≥6 years	1.00	1.00	1.00
Training/skill			
Status of training			
Yes		0.691 (0.48 to 0.994)*	0.715 (0.496 to 1.031)
No		1.00	1.00
Computer efficacy			
Beginner			0.689 (0.525 to 0.904)*
Advanced users			1.00

Source: Agyemang, 2021.
1.00=reference category; sample (N)=1126.
p<0.05.
LHIMS, lightwave health information management system.

Findings from the study revealed that the LHIMS enhances service delivery efficiency. The health professionals who participated in the study indicated that using the LHIMS lessens a patient's time spent at the unit and facilitated quick task execution, as well as assists in giving the patients the proper care. Admittedly, these results are consistent with the 2005 and 2010 National E-Health Strategy Policy's objective[27] and with the international standard, HealthIT.Gov[28] which suggests that an EHR system should offer quick access to patient records and efficient job execution in addition to providing accurate, full and up-to-date patient information at the point of care. The findings show that the LHIMS has these features and is now deployed and used widely within the health sector of Ghana. However, results from Hodgson *et al*[29] research reported inefficiencies of EHRs adoption such as system users being permanently connected to a computer and using multiclick diagnostic chart navigations which make the use of EHR systems by health professionals undesirable. However, the findings from our study indicated the contrary. The reasons that might account for the differences in literature may be due to several factors including, the type of EHR software deployed, the design of the system interface, personal factors such as age, sex, work experience, training prior to system use and type of profession.[30] For instance, Shanafelt *et al*[30] argue that several factors influence the efficient use of EHR systems. According to the technology acceptance model by Davis,[21] external factors such as age, gender and organisational factors are theorised to influence the perceived usefulness (efficiency) of an EHR system. As a result, this current study hypothesised that health professional's efficient use of the LHIMS is influenced by sociodemographic characteristics (age, sex, educational qualification and years of work experience), professional characteristics (staff category, place of training and institution of training) and computer self-efficacy. The results of the multivariate analysis for sociodemographic characteristics (age, sex, educational qualification and years of work experience) of health professionals and the efficient use of EHRs revealed that age, sex and educational qualification had an insignificant effect on the efficient use of EHR. However, years of work experience were the only sociodemographic characteristic that was found to have a statistically significant influence on the efficient use of LHIMS. The results agree with the findings from Adedeji *et al*,[31] Khairat *et al*[32] and Bae and Encinosa.[33] Adedeji *et al* in their study found a significant association between the use of EHR and age, availability of computer systems, years of working experience and training of users.[31] The results of their study are in contrast with that found in this study except in terms of years of work experience which was found to have no significant effect on efficiency in the use of EHR among health professionals.[31] Khairat *et al* in their study examined how doctors' performance, efficiency, perceived workload, happiness and usability of the EHR differed depending on their age, gender, professional function and years of experience with the EHR.[32] They found some differences in efficiency among male and female physicians.[32] The data showed that female physicians are more efficient in using EHRs as they used the EHR's general search bar and filters, which resulted in a more efficient search, and this means that differences in sex among health professionals play a role in their efficient use of EHR.[32] This finding contrasts with the one obtained in this study. However, even though sex, in general, was found to have no significant effect on the efficient use of EHR, the results, show that females in practice will be able to use the LHIMS-EHR more efficiently as compared with their male colleagues. This somewhat contrasting analysis may be due to the bivariate analysis which showed that the sex of health professionals has an association with their efficient use of EHR.

Bae and Encinosa[33] in their study revealed that age and years of work experience matter in the efficient use of an EHR system.[33] They found that older physicians who have more years of experience in the field were better at integrating EHR into clinical practice as compared with younger physicians with just a few years of work experience.[33] Their study, therefore, provides support for the finding that years of work experience have played a major role in the efficient use of LHIMS by health professionals but contrasts with the finding that the age of health professionals does not affect how efficiently they use EHR. These findings indicate that not all external factors (age, sex and education) in the technology acceptance model by Davis[21] may predict differences in the efficient use of the LHIMS and the variation in the literature is dependent on the type of EHR software adopted.

Aside from social demographic characteristics, the multivariate analysis of professional characteristics and efficient use of the LHIMS revealed an insignificant association between professional type and the institution where health professionals receive their training and efficient use of the LHIMS. However, the bivariate analysis of professional type and efficiency in the use of the LHIMS showed a significant association between the two. This means that the professional characteristics of health professionals do not affect how efficiently respondents used the LHIMS taking into consideration other variables such as age, sex, education and years of work experience. Similar findings are noted in the works of Nandikove *et al*.[34] The researchers indicated no significant differences among professional types concerning the use of the EHR system in Kakamega County, Kenya.[34]

The multivariate analysis of training/computer efficacy showed that computer efficacy had a significant effect on the efficient use of LHIMS whereas training was found to have no significant effect. This means that health professionals cannot use the LHIMS efficiently without computer efficacy. However, whether they receive training on using EHR systems does not greatly enhance their efficiency. Contrarily, Butcher found different results on training and professional type.[35] According to Butcher, health professionals who received training in EHR systems used relatively less time working in the EHR

systems as compared with when they had not received any training.[35]

However, the bivariate analysis showed a significant relationship between the two even though the multivariate analysis revealed there is no causal relationship between the two. It can therefore be inferred that even though training does not significantly affect health professionals' efficiency with LHIMS, it can go a long way to improve their proficiency in the use of the system. This may be because health professionals may not be able to use EHR systems most optimally as they may not have received any prior training on EHR systems in their training institutions. It may also be that the training was not effective since most respondents received just a day of training and some did not receive training at all but relied on their colleagues for support in using the LHIMS. Both situations necessitate training specific to the EHR system being used at their health facility for improved proficiency.

The results of the study pertaining to service delivery efficiency revealed that sociodemographic characteristics and the computer efficacy of health professionals are very important factors if they are to use the LHIMS efficiently. This implies that hospital governing bodies and health administrators will need to make sure that all health professionals that will be posted or hired have taken some general computing courses as, without it, efficient use of the LHIMS at the facility level will be significantly affected. Also, the MoH and its Agencies including hospital managers need to ensure that new entrant of health professionals with little or no work experience are to be trained and paired with experienced system users of the LHIMS. This is to ensure that the inefficiencies identified with the use of EHR systems by other researchers will not be experienced at the centre as they have serious repercussions for patients as well as the institution.

CONCLUSION

It can be implied from the results of descriptive statistics, LHIMS deployment has enhanced service efficiency. The bivariate analysis revealed that there is an association between training prior to the use of the LHIMS and the efficient use of the system. However, at the multivariate level, training prior to the use of LHIMS was not statistically significant but computer efficacy and years of work experience were statistically significant. This result implies that not only should health professionals be trained on the use of the LHIMS but for professionals to be more efficient in the use of the LHIMS, they should be trained in general computing skills to improve their computer efficacy. Also, findings imply that health professionals with more work experience need to support their colleagues with little work experience in using the LHMIS to enhance the overall efficiency of the institution. Also, aside from the general training given to all the health professionals at a health facility, health professionals can seek individualised IT training based on their professional type and information needs for optimum proficiency in the use of the LHIMS by way of increased confidence in all healthcare activities and overall time reduction in the system among health professionals.

Contributors EA, KE-D, ABA-G and EKA were responsible for the conception and design of the study. EA was responsible for the conception and design of the survey questions, and the acquisition, and interpretation of data. EA conducted statistical analyses and drafted tables, and figures. EKA wrote the original manuscript of the paper. EA, KE-D, ABA-G, EKA, POA and JBD reviewed and edited the manuscript. The final version of the manuscript was approved by all contributing authors. EKA is the guarantor for this study.

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Ethics approval This study involves human participants and the study was conducted in accordance with the guidelines of the University of Cape Coast Institutional Review Board (IRB), Ghana Health Service Ethics Review Committee (GHS-ERC) and the Cape Coast Teaching Hospital-IRB. Participants gave informed consent to participate in the study before taking part.

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An online glaucoma educational course for patients to facilitate remote learning and patient empowerment

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ABSTRACT

In both face-to-face and teleophthalmology glaucoma clinics, there are significant time constraints and limited resources available to educate the patient and their carers regarding the glaucoma condition. Glaucoma patients are often not satisfied with the content and amount of information they receive and have demonstrated a substantial lack of knowledge regarding their condition. Innovative educational tools that facilitate accessible digital remote patient education can be a powerful adjunct to empower patients in becoming healthcare partners.

We describe the development of a free, comprehensive, multimodal online glaucoma patient education course for adults with glaucoma, their family and friends and carers, with the aim of providing a readable resource to aid remote learning and understanding of the condition.

The working group for the development of the course comprised of consultants, medical practitioners and education specialists and expert patients. Given the specialised nature of ophthalmology and glaucoma, certain aspects can be difficult to conceptualise, and, therefore, clear and adequate explanations of concepts are provided in the course using diagrams, flow charts, medical illustrations, images, videos, written text, analogies and quizzes.

The course is available in a short and long version to suit different learning needs which take approximately 2 hours and 10 hours to complete respectively. The contents list allows course takers to find sections relevant to them and it can be taken anywhere, as long as there is Internet access.

We invite you to share this resource with your patients and their families, friends and carers.

THE NEED FOR AN ONLINE GLAUCOMA EDUCATION COURSE

Glaucoma is the most common cause of irreversible visual impairment and its prevalence is on the rise, with the number of people affected estimated to be over 100 million by 2040.[1] It is a chronic condition characterised by progressive damage to the optic nerve with characteristic visual field loss requiring lifetime monitoring and care. Glaucoma has a substantial and detrimental effect on many aspects of daily living,[2] and accounts for 23% of all hospital eye service follow-ups and 13% of new referrals.[3] This places a huge demand on glaucoma outpatient clinics. Teleophthalmology now plays a vital role in increasing capacity for the continued delivery of glaucoma care in developed parts of the world. Two models of teleophthalmology are in place: synchronous, which involves a teleconsultation with a medical professional, and asynchronous, whereby the patient undergoes diagnostic tests carried out by a specialised medical assistant which are reviewed by a medical professional within a defined period and a written report is sent to the patient.[4]

In both face-to-face and teleophthalmology clinics, there are significant time constraints and limited resources available to educate the patient and their carers regarding the condition. Importantly, guidance from both the General Medical Council,[5] and National Institute for Health and Care Excellence stipulate that patients should be given the information they want or need in a way they can understand and that healthcare professionals should provide "relevant information in an accessible format" as well as "practical information and advice" on various issues surrounding their condition.[6] The majority of current practice involves issuing leaflets to patients and their carers written by the hospital or glaucoma charities in paper format, which is done inconsistently.

Furthermore, it is concerning that in asynchronous review clinics there is no direct doctor-patient contact, further limiting an opportunity for patient education and this is one of the main areas in which patient satisfaction and acceptance of these clinics are negatively impacted. Drawbacks of asynchronous review clinics include a 20% decrease in patient adherence to medication, as well as 20% of patients complaining regarding not seeing a doctor; with 2% stating that there was a detrimental effect on the doctor-patient relationship.[7] Patients have expressed concern regarding the lack of immediate

feedback and the absence of being reviewed by a doctor on the day,[4] with 10% reporting that they were not happy to receive clinic results by post but would have been happier to wait longer to see a doctor or optometrist, as well as expressing a dissatisfaction with not having the opportunity to ask questions about their condition.[8] This is even more pertinent to patients from different ethnic groups, where English is not the first language, or who are elderly. Adoption of a system that would allow the immediate resolution of queries and for clinical letters to be more patient-friendly with better explanation of technical terms would be beneficial.[9] Anecdotally, clinicians performing these clinics often produce their own personal letter templates to explain conditions and concepts, and although these may be helpful, they are often not standardised, complete or patient-friendly and there is no opportunity to physically hand out paper leaflets, although sometimes these are posted to the patient with their letter.

Patient education is an essential tool for clinicians to use to empower patients in becoming more autonomous concerning their health and treatment. It helps patients make better choices in line with their values and encourages them to become healthcare partners.[10] Education and exchange of information is pivotal to shared decision making; the importance of which has been previously described, including the positive impact it has on treatment outcomes.[11] Patients with a chronic disease often have inadequate knowledge about their disease.[12 13] Glaucoma patients are often not satisfied with the content and amount of information they receive and have demonstrated a substantial lack of knowledge.[14] A Glaucoma Patient Day held in the United Kingdom (UK),[12] with 296 attendees revealed that the attendees ascribed great importance to the usefulness of the event for their learning as well as stating that their understanding of glaucoma had significantly improved following the event. The patients wanted to know more about glaucoma, in particular what effect it has on them, how they can help themselves and how best to administer their eyedrops.

Well-informed patients better understand their prognosis and manage their disease better. They are also more compliant and more likely to cope effectively with the changes the illness causes.[12] Informed patients express greater satisfaction and experience less anxiety, less adverse event rates and less treatment regret.[15] In glaucoma, low health literacy is associated with decreased adherence to treatment regimens and increased difficulty with eye drop administration.[16] Furthermore, when glaucoma patients received a synchronous coaching session on eye drop instillation, 92% of patients who had received teaching found it useful, emphasising that health coaching is an effective strategy in empowering patients.[13]

The use of video-based media appears to be effective in improving patient understanding and in certain cases improve overall outcomes.[17] 63% of internet users seek medical information and support online in the UK.[18] While online resources providing general information on glaucoma are easily accessible, patients may not differentiate resources that are not operated by reputable sources. Given the increasing utilisation of online sources for health information, the readability of online patient education materials is increasingly important. 15% of UK adults have reading levels below 9 to 11 year olds (year 6).[19] A systematic review of the literature revealed that ophthalmic patient education materials are consistently written at a level that is too high for many patients to understand.[20] The majority of online glaucoma reading materials are written at a year 11 to 12 level; which is far above the recommended readability parameter of a year 8 reading level.[21] Furthermore, Black and Latino adults, individuals over 65 years old, and those with low-income levels are three times more likely to lack digital literacy compared with their White counterparts.[22]

There is an urgent need for innovative, comprehensive and accessible educational tools that are comprehensible, to facilitate digital remote patient education and act as a powerful adjunct to face-to-face and teleophthalmology clinics. To our knowledge, there are currently no glaucoma patient education courses available that offer comprehensive, accessible, multimodal education at appropriate reading levels. We developed an online glaucoma patient education course to meet this need.

COURSE DEVELOPMENT

Our primary aim was to produce a free, multimodal, comprehensive and accessible resource to aid remote learning and understanding of the glaucoma condition. The secondary aim was to provide a resource for glaucoma practitioners to have to hand to direct patients to when wanting to provide patients with more comprehensive information, or when reviewing patients asynchronously. The primary target audience is adults in the UK with glaucoma, their family, friends and carers, although the course can be used globally by English-speaking adults. The pedagogical framework used to develop the course was the constructivist approach.

The working group comprised of 2 consultants, 4 glaucoma fellows, allied health professionals including two nurses, 1 eye clinic liaison officer, 2 optometrists and two pharmacists, 2 education specialists and 5 expert patients from the UK. During the planning and design stage, patients were interviewed to collect information regarding what they wished to know about, encouraging patient-centred education, which even though advocated by the GMC, and popular in medical education, is novel to patient education development.

The development stage involved authoring of the course material by SH, CI and AB and review by SH, NM, CI, AB, MP, DM and RGM. Writing the material involved reviewing glaucoma literature and writing at the year 7 reading level. Given the specialised nature of ophthalmology and glaucoma, certain aspects can be difficult to conceptualise, and, therefore, clear and adequate explanations of concepts are provided using diagrams, flow

charts, medical illustrations, images, videos, short films, written text and analogies. The content was formatted on the Articulate Rise platform by the educational specialists. The main challenge was getting the language level correct for patients to understand. Non-medical persons and patients reviewed the content and informed the editing stage to improve ease of understanding.

The educational content was defined into various components and includes the following sections: what is glaucoma, glaucoma epidemiology, risk factors, diagnosis, living with glaucoma, glaucoma treatment (including medications, medication education and how to instil your eyedrops, laser, surgery and alternative therapies such as diet and lifestyle advice), different types of glaucoma, future advances in glaucoma and information on support services, charities and low vision help. There is also a 'patient voice' section in which patients were interviewed about their glaucoma journey and these video extracts are included within the course. We excluded childhood/congenital glaucoma. There is a pre- and post- course quiz to evaluate the learning that has taken place and provide feedback.

The course is available in a short and long version to suit different learning needs which take approximately 2 hours and 10 hours to complete respectively. The contents list allows course takers to find sections relevant to them and it can be taken anywhere, with easy access to the information at any time as long as there is Internet access. Reasonable adjustments were made for users who may be visually impaired or have limited English proficiency. These included ensuring the content have 'alt text' for those who use screen readers so that the text can be explained to them, as well as recording some of the content script in a number of languages such as Arabic, Turkish and Spanish, to make it as accessible as possible to people from different backgrounds. The course was approved by the hospital Information Governance department and in the final stage, was marketed through the hospital communications to different departments, via the hospital charity and also a short radio interview by SH and CI.

ACCESSING THE COURSE

The course can be accessed easily for free via Google, by typing in the words "Glaucoma" + "Moorfields Education" in the search engine or by accessing the following URL directly [https://checkout.moorfields.nhs.uk/product?catalog=GLAUCOMA]. We invite you to use this resource for the benefit of your patients, their families, friends and carers, by sharing the course with them.

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Experiences in aligning WHO SMART guidelines to classification and terminology standards

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ABSTRACT

Objectives Digital adaptation kits (DAKs) distill WHO guidelines for digital use by representing them as workflows, data dictionaries and decision support tables. This paper aims to highlight key lessons learnt in coding data elements of the antenatal care (ANC) and family planning DAKs to standardised classifications and terminologies (CATs).

Methods We encoded data elements within the ANC and family planning DAKs to standardised CATs from the WHO CATs and other freely available CATs.

Results The coding process demonstrated approaches to refine the data dictionaries and enhance alignment between data elements and CATs.

Discussion Applying CATs to WHO clinical and public health guidelines can ensure that recommendations are operationalised in a digital system with appropriate consistency and clarity. This requires a multidisciplinary team and careful review to achieve conceptual equivalence between data elements and standardised terminologies.

Conclusion The systematic translation of guidelines into digital systems provides an opportunity for leveraging CATs; however, this approach needs further exploration into its implementation in country contexts and transition into machine-readable components.

INTRODUCTION

With increased investments into digital systems, the adoption of standardised classifications and terminologies (CATs) is critical for establishing clarity and consistency when encoding, documenting and exchanging information on health-related events.[1 2] Classifications are defined as 'an exhaustive set of mutually exclusive categories to aggregate data at a pre-prescribed level of specialisation for a specific purpose and used to categorise concepts for the purposes of systematic recording or analysis.[3 4] Terminology is a set of designations 'required directly or indirectly to describe health conditions and healthcare activities' to enable accurate specification and unambiguous communication across health settings.[1–4] CATs provide a common language to describe the care and treatment of patients using standardised terms. The use of fit-for-purpose and freely available CATs are important for representing information in a consistent manner, enabling the storage, retrieval and meaningful analysis of health information and exchange of information across facilities.[5]

In 2021, the WHO established the SMART (SMART guidelines stands for standards-based, machine-readable, adaptive, requirements-based and testable) guidelines approach to reinforce clinical, public health and data recommendations through digital systems.[6] CATs are an integral part of WHO SMART guidelines for ensuring consistency and minimising ambiguity when translating guideline content for digital systems. WHO digital adaptation kits (DAKs), which are one part of the SMART guidelines, define the workflows, core data elements and decision-support logic and other key requirements for digital systems.[6 7] Each DAK includes a detailed data dictionary containing a comprehensive list of data elements, which are mapped to appropriate, open-access CATs (see figure 1).[8 9]

Despite the value of CATs, the process of incorporating them into point-of-care digital systems may be overlooked or done inadequately for a variety of reasons[1]: perceptions of being resource and time intensive, not understanding the value or return on investment, limited access to clinical terminologists with specialised skillsets and uncertainty in managing mismatches between commonly used medical terms and what is available in established CATs. International public CATs, which are freely available with full functionality, are included in the DAK data dictionaries to overcome challenges associated with the use of these standards. The coded data dictionaries, along with the decision support logic, form the basis for more structured and

[ANC] Activity ID	Data element label	ICD-11 Code	ICD-11 URI	ICD-10 Code	LOINC version 2.68 Code	ICHI Code	ICHI URI	ICF Code
ANC.B6. Collect woman's profile and history	Past pregnancy complications							
ANC.B6. Collect woman's profile and history	Gestational diabetes mellitus	JA63.2	http://id.who.int/icd/entity/1320503631	O24.4	45636-8	Not classifiable in ICHI		Not classifiable in ICF
ANC.B6. Collect woman's profile and history	Eclampsia	JA25.3	http://id.who.int/icd/entity/250375350	O15.9	58297-3	Not classifiable in ICHI		Not classifiable in ICF
ANC.B6. Collect woman's profile and history	Pre-eclampsia	JA24.Z	Parent URI for residual code JA24.Z http://id.who.int/icd/entity/229121159	O14.9	58297-3	Not classifiable in ICHI		Not classifiable in ICF
ANC.B7. Check symptoms and follow-up	Persistent physiological symptoms							
ANC.B7. Check symptoms and follow-up	Abnormal vaginal discharge	MF3A	http://id.who.int/icd/entity/2123556104	N89.8	70380-1	Not classifiable in ICHI		s63033
ANC.B7. Check symptoms and follow-up	Constipation	ME05.0	http://id.who.int/icd/entity/502284069	K59.0	28235-0	Not classifiable in ICHI		b525
ANC.B7. Check symptoms and follow-up	Contractions	JA8D.Z	Parent URI for residual code JA8D.Z http://id.who.int/icd/entity/1432083898	O47.9	56866-7	Not classifiable in ICHI		b28012
ANC.B.10.6 Risk reduction & general counselling	Risk reduction & general counselling							
ANC.B.10.6 Risk reduction & general counselling	Gestational diabetes mellitus (GDM) risk counselling conducted	QA1Y	Parent URI for residual code QA1Y http://id.who.int/icd/entity/1003660192	Z71.8	Not classifiable in LOINC	ET2.PP.ZZ	https://mitel.dimi.uniud.it/ichi/#http://id.who.int/ichi/entity/1056058828	Not classifiable in ICF
ANC.B.10.6 Risk reduction & general counselling	Pre-eclampsia risk counselling provided	QA1Y	Parent URI for residual code QA1Y http://id.who.int/icd/entity/1003660192	Z71.8	Not classifiable in LOINC	HT2.PP.ZZ	https://mitel.dimi.uniud.it/ichi/#http://id.who.int/ichi/entity/486446165	Not classifiable in ICF
ANC.B.10.6 Risk reduction & general counselling	Counselling conducted on HIV risk	QA14	http://id.who.int/icd/entity/1763891540	Z71.7	Not classifiable in LOINC	DTB.PP.ZZ	https://mitel.dimi.uniud.it/ichi/#http://id.who.int/ichi/entity/1632570873	Not classifiable in ICF

Figure 1 Overview of the ANC DAK data dictionary with data element label, definition and CAT code sets. ANC, antenatal care; CATs, classifications and terminologies; DAK, digital adaptation kit; ICD, International Statistical Classification of Diseases; ICHI, International Classification of Health Interventions; ICF, International Classification of Functioning, Disability and Health; LOINC, Logical Observation Identifier Names and Codes

machine-readable guidance for countries through the use of Health Level Seven Fast Healthcare Interoperability (FHIR) standards.[6] As such, the data dictionaries within the DAKs are a valuable first step in moving toward the specificity that is needed to support semantic interoperability for meaningful data exchange and continuity of care.

This paper describes the lessons learnt in coding data elements of the antenatal care (ANC)[9] and family planning DAKs[8] to standardised CATs and strategies for avoiding common pitfalls and improving the process.

METHODS

WHO teams that developed the DAKs for each health area (ANC or family planning) provided an Excel of the data dictionary with each data element presented in terms of label, data type, input options, validation conditions, skip logics and calculations.[8 9] Additional columns were included for the classification specialist to provide corresponding code sets for each data element. As the main aim of the SMART guidelines is to accelerate guideline adoption, the DAKs were first drafted based on the clinical health content needs and subsequently aligned to the CATs.

Coding data elements to CATs

The classification specialist mapped data elements to the CATs listed in table 1 employing online browsers for each code system.[5 10–13] After an initial coding by the classification specialist, data elements and corresponding concepts were reviewed during virtual meetings with respective health programme experts. Each new DAK was compared against previous DAKs for data element consistency in terms of labels, descriptions and response options. The terminology specialist first reviewed the data dictionaries and proposed a code derived from a search of the CATs based on an understanding of the data element and the description. The health programme leads reviewed the proposed codes through comments on the data dictionary spreadsheet and discussed questions that emerged during weekly calls to resolve issues and ensure the assigned code was as accurate as possible considering the governance and controlled vocabulary constraints of CATs. The final code mappings were approved by the health programme leads.

RESULTS

Refining consistency and construction of data dictionaries

Coding CATs led to refinements of the data dictionaries to provide greater specificity (eg, 'diabetes mellitus' was expanded to include type 1, type 2, gestational and other diabetes mellitus in the ANC DAK data dictionary) or capture a broader range of data. Several data elements, such as 'nausea/vomiting', which may be an appropriate data entry from a clinical perspective in pregnancy, were separated into two data elements as each has a different code.

Table 1 Description of the freely available classifications and terminologies used in the DAKs

Classification and terminology type	Publisher	Description
WHO classifications and terminologies		
International Statistical Classification of Diseases and Related Health Problems (ICD-10/ICD-11)	WHO	Defines and classifies diseases, disorders, injuries and other related health conditions, listed in a comprehensive, hierarchical fashion.[5]
International Classification of Health Interventions (ICHI)	WHO	Common tool for reporting and analysing health interventions for statistical purposes.[12]
International Classification of Functioning, Disability and Health (ICF)	WHO	Framework for measuring health and disability at both individual and population levels also includes a list of environmental factors.[13]
Other classifications and terminologies		
Logical Observation Identifier Names and Codes (LOINC)	Regenstrief Institute	Catalogue of measurements, including laboratory tests, clinical measures like vital signs and anthropometric measures, standardised survey instruments and more.[10]
Systematised Nomenclature of Medicine (SNOMED—Global Patient Set)	SNOMED International	Clinical healthcare terminology is designed to provide a core general terminology for electronic health record systems.[11] SNOMED CT is a propriety code system, and as such the browser used for the coding of the DAKs was the openly available, GPS, which includes a non-hierarchical subset of SNOMED CT codes.

DAKs, digital adaptation kits.

We also reviewed the consistency of data elements within a DAK, and across several DAKs, to standardise the data labels. The effort to reconcile inconsistencies varied based on the amount of data elements in the data dictionary and became incrementally easier as some of the previously reconciled data mappings could be repurposed for new DAK areas.

Reconciling inexact matches between data elements and code systems

There were frequent instances in which the data element label or description did not match directly with the standardised framing in the CATs. In these cases, we assigned a 'best fit' code set for coding purposes, with an explicit indication in the data dictionaries. For example, in the family planning data dictionary, WHO recommendations use the term 'insulin/non-insulin dependent diabetes', due to the potential interactions between insulin and hormonal contraception. However, terms available within CATs are 'type 1/type 2 diabetes'. Ultimately, the insulin/non-insulin dependent categories were retained but coded to type 1/type 2 diabetes as 'best fit'.

Usability and applicability of CATs

Each CAT presented unique challenges and depended on clinical term(s) used to search for concepts. Searches generated different responses based on specificity of terms included. For example, if 'acute' or 'chronic' was added as part of the search, it rendered a different search output compared with when these terms were not included, depending on the granularity of the CATs. As a result, consistency in the search terms and crosschecking different options is necessary to ensure coding to appropriate clinical concepts.

We also observed that some disease conditions and contextual elements were more consistently classifiable using International Statistical Classification of Diseases (ICD-11). In the ANC DAK, International Classification of Functioning, Disability and Health did not have much applicability, which was expected, given that it is a classification for functioning and disabilities, and pregnancy does not traditionally fit in either category. However, some data elements do not need to be coded and will need to be retained simply as the value entered (eg, age, weight) to be useful for clinical purposes. Mapping of demographic (eg, age), chronological (eg, date of visit), contextual data elements (eg, facility location) and descriptions did not align with the structure of CATs. For example, there is no code in the ICD-11 for 'Gestational Age' as a general concept. However, there is a standardised range of codes for 'Duration of Pregnancy' (https://icd.who.int/dev11/l-m/en#/http://id.who.int/icd/entity/920837303) which could be applied.

DISCUSSION

This process uncovered lessons in applying CATs. Achieving conceptual equivalence between the data elements in the data dictionary and reference standards emerged as one of the major learnings and highlighted the need for strengthening linkages between guideline development and health informatics. As clinical and public health guidelines are often not written with health informatics data modelling requirements in mind,

the challenges faced are not unexpected. However, this also offers insights on how linkages can be strengthened between these complementary domains to support provision of health services in the digital age while ensuring formal representation through CATs.

The enhanced understanding of the coding relationships to various CATs presents opportunities for refining the process and adhering to the principles and best practice for WHO-FIC Classifications and Terminology Mapping (3). Additionally, this coding exercise would need to be further reviewed when adapting the DAKs to country contexts and into machine-readable guidelines to ensure the consistency in the terms is preserved. Future DAKs could also benefit from a master spreadsheet that standardises data elements repeated across sections, to reduce the time and potential inconsistencies in coding. This would also facilitate the automated creation of FHIR profiles based on the DAK content and codification into machine-readable artefacts in the form of a FHIR Implementation Guide.[14]

CONCLUSION

As WHO recommendations are often not conceived with health informaticians, the SMART guidelines approach of systematically applying CATs to WHO clinical and public health recommendations for use in digital systems represents both a daunting and pathfinding effort. Through this endeavour, we highlight mechanisms for leveraging standardised CATs to facilitate meaningful data exchange for continuity of care, measurement, and maximise benefits from countries' digital implementations.

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Telehealth interventions during COVID-19 pandemic: a scoping review of applications, challenges, privacy and security issues

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ABSTRACT

Background The COVID-19, caused by the SARS-CoV-2 virus, proliferated worldwide, leading to a pandemic. Many governmental and non-governmental organisations and research institutes are contributing to the COVID-19 fight to control the pandemic.

Motivation Numerous telehealth applications have been proposed and adopted during the pandemic to combat the spread of the disease. To this end, powerful tools such as artificial intelligence (AI)/robotic technologies, tracking, monitoring, consultation apps and other telehealth interventions have been extensively used. However, there are several issues and challenges that are currently facing this technology.

Objective The purpose of this scoping review is to analyse the primary goal of these techniques; document their contribution to tackling COVID-19; identify and categorise their main challenges and future direction in fighting against the COVID-19 or future pandemic outbreaks.

Methods Four digital libraries (ACM, IEEE, Scopus and Google Scholar) were searched to identify relevant sources. Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) was used as a guideline procedure to develop a comprehensive scoping review. General telehealth features were extracted from the studies reviewed and analysed in the context of the intervention type, technology used, contributions, challenges, issues and limitations.

Results A collection of 27 studies were analysed. The reported telehealth interventions were classified into two main categories: AI-based and non-AI-based interventions; their main contributions to tackling COVID-19 are in the aspects of disease detection and diagnosis, pathogenesis and virology, vaccine and drug development, transmission and epidemic predictions, online patient consultation, tracing, and observation; 28 telehealth intervention challenges/issues have been reported and categorised into technical (14), non-technical (10), and privacy, and policy issues (4). The most critical technical challenges are: network issues, system reliability issues, performance, accuracy and compatibility issues. Moreover, the most critical non-technical issues are: the skills required, hardware/software cost, inability to entirely replace physical treatment and people's uncertainty about using the technology. Stringent laws/regulations, ethical issues are some of the policy and privacy issues affecting the development of the telehealth interventions reported in the literature.

Conclusion This study provides medical and scientific scholars with a comprehensive overview of telehealth technologies' current and future applications in the fight against COVID-19 to motivate researchers to continue to maximise the benefits of these techniques in the fight against pandemics. Lastly, we recommend that the identified challenges, privacy, and security issues and solutions be considered when designing and developing future telehealth applications.

INTRODUCTION

COVID-19, caused by the SARS-CoV-2 virus, was first identified in China in December 2019 and later became a pandemic.[1 2] When this manuscript was finalised (12 June 2022), globally, the total number of infected cases had reached 540 318 million and over 6.331 million people had died.[3]

Telehealth refers to the delivery of healthcare particularly preventive and primary healthcare over a distance. Furthermore, it has been described as the use of medical information exchanged from one site to another via electronic communication to improve a patient's health.[4] It can also be defined as distributing health-related services and information through electronic information and telecommunication technologies. It enables long-distance patient and clinician care, contact, reminders, advice, education, intervention and remote admissions. During the spread of COVID-19, several technological interventions were introduced to help manage the pandemic (eg, utilisation of digital tools to combat the COVID-19 pandemic[5] such as internet of things (IoT), drones, artificial intelligence (AI), blockchain and 5G).[6]

When the COVID-19 pandemic pushed the healthcare system to its breaking point, telehealth appeared as a critical alternative for burdened physicians and organisations.[7] Telehealth was a valuable tool in the fight against the COVID-19 pandemic.[8 9] Functions such as remote patient monitoring,[10–12] communication and counselling,[13] psychotherapy,[14] telerehabilitation, consultation,[15] and telementoring[14] became extremely popular, useful features for delivering healthcare. As telehealth became characterised by technologies, users, environment, processes and organisations, telehealth became multilayer healthcare system support. However, increased data privacy issues,[8 16] human error, social factors, psychosocial factors, technological issues and other external factors are bringing about the need for better control of telehealth applications.

In this study, we have conducted a scoping review covering four different databases: ACM, IEEE, Scopus and Google Scholar; and identified 28 telehealth intervention challenges/issues. The challenges/issues were categorised into technical (14), non-technical (10), and privacy, and policy issues (4). The issues reported in this article comprise both technical and behavioural security concerns, issues such as attacks, vulnerabilities, weaknesses are examples of technical security issues found in the literature. While ethical issues such as 'a clinician may improperly exploit patient data to conduct genetic or biological investigations or dispense medications that violate approved regulations' are examples of behavioural security issues reported in our reviewed articles. Furthermore, the reported telehealth interventions were classified into two main categories: AI-based and non-AI-based interventions. The distinction between AI and non-AI telehealth is significant since it represents the degree of automation and intelligence engaged in healthcare service delivery. Traditional telehealth services that rely on basic videoconferencing, remote monitoring and other communication technologies to support interactions between patients and healthcare practitioners are referred to as non-AI telemedicine. In contrast, AI-enabled telehealth uses powerful machine learning algorithms, natural language processing and other AI techniques to evaluate patient data, develop insights and deliver individualised suggestions to patients and healthcare professionals.[17]

Moreover, AI-enabled telehealth has the potential to greatly improve healthcare delivery quality and efficiency. AI algorithms, for example, may assist clinicians in efficiently analysing massive quantities of patient data, identifying patterns and trends, and making correct diagnoses.[17 18] Its virtual assistants and chatbots may also give real-time assistance, support and education to patients, which can enhance patient engagement, self-management and adherence to treatment programmes. Nevertheless, it is also critical to acknowledge the possible dangers and obstacles connected with AI-enabled telehealth, such as data privacy concerns, algorithmic bias and the ethical implications of depending on machine-based decision-making in healthcare. As a result, it is vital to carefully weigh the benefits and downsides of both AI and non-AI telehealth systems, as well as to ensure that proper protections are in place to protect patients and preserve the highest standards of care. Thus, our study aimed to achieve the following research questions.

Research questions/objectives

The main objective of this survey is to identify and classify telehealth interventions that emerged during COVID-19 pandemic, document their challenges, and policy, privacy and security issues. This is to motivate researchers to continue to maximise the benefits of these techniques to fight COVID-19 and other diseases, and as well consider the issues/solutions reported when designing and developing future telehealth applications. Therefore, this study aimed to answer the following research questions to address this goal:

- What are the distinct types of telehealth interventions that appeared and became popular during the COVID-19 pandemic?
- What are telehealth intervention challenges when fighting the COVID-19 pandemic?
- What are telehealth intervention policy, privacy and security issues specific to fighting the COVID-19 pandemic?

Research contributions

The contributions of this study can be summarised as follows:

- Identification, classification and analyses of the various kinds of telehealth interventions that appeared or were adopted during COVID-19;
- Identification, categorisation and analyses of the challenges of telehealth interventions that appeared or were adopted during COVID-19.
- Identification of policy, privacy and security issues about telehealth interventions aiding in fighting the COVID-19 pandemic.
- Identification of remedies available for tackling reported telehealth intervention policy, privacy and security issues when fighting the COVID-19 pandemic.

Previous studies have attempted to survey the telehealth interventions that emerged during the COVID-19 pandemic and the challenges associated with them.[17 19–22] These studies can be classified according to their study design and the main issues reported. Some studies conducted a systematic mapping study and focused solely on telehealth security issues,[23] while others have conducted systematic reviews on the use of telehealth during COVID-19, emphasising the features, benefits and effects of the reviewed systems.[19–22] However, some of these studies have only covered a few articles or general challenges without specifically addressing privacy, policy, and security issues and solutions.[19–21] Additionally, some studies have had limited search comprehensiveness by covering only a few databases,[21] or a specific type of telehealth intervention, such as AI-based systems[17]—a scoping

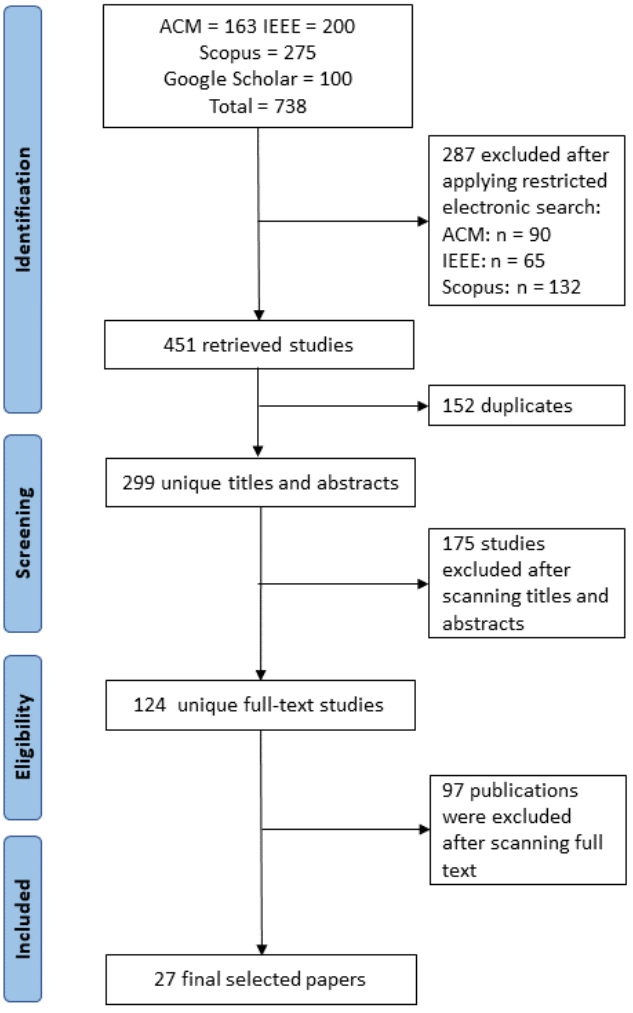

Figure 1 PRISMA chart for included studies. PRISMA: preferred reporting items for systematic reviews and meta-analyses.

review. In contrast, our study covered both AI-based and non-AI-based systems, and to the best of our knowledge, none of the existing studies have combined all of the above four contributions. Hence, this study can be considered the first comprehensive study to identify, classify, discuss and analyse the telehealth interventions, their associated challenges and issues, as well as discussing societal considerations (privacy, policy, security) with respect to various system types, technical and behavioural issues. Our study also highlights how the challenges/issues imposed by the pandemic boosted research and technology towards the improvement and diffusion of telehealth solutions.

METHODS

PRISMA Extension for Scoping Reviews (PRISMA-ScR)[24] was used as a guideline procedure to develop this comprehensive scoping review. As illustrated in figure 1, the search procedure for this scoping review was extensive. The search execution was performed between 13 December 2021 and 15 December 2021. Table 1 lists the publication venues of the final included articles. The detailed procedure of the method followed is provided as online supplemental material (Methodology).

Table 1 Publication venue of the selected papers

#	Venue	Type	# of publications
1	*IEEE*	Journal	8
2	*IEEE*	Conference	3
3	*IEEE*	Symposium	1
4	*ACM*	Journal	2
5	*ACM*	Conference	4
6	*ACM*	Workshop	1
7	*JMIR*	Journal	2
8	*BMJ*	Journal	1
9	*JAMA*	Journal	1
10	*New England Journal of Medicine Jama*	Journal	1
11	*Medknow Publications*	Journal	2
12	*SciELO Brasil*	Journal	1
	Total		27

RESULTS

Types of telehealth applications

Several studies presented telehealth interventions and their applications. These studies can be classified into two main categories according to their mode of application: The first category is AI-based; this category includes AI-based systems incorporating IoT and mechanical aspects and reported applications using machine learning or deep learning neural networks. The second category includes applications that do not employ any AI neural networks and are therefore categorised as non-AI based.

The following subsections present a general overview of some AI-based and non-AI-based telehealth interventions from our included studies.

AI-based techniques in fighting against COVID-19

This section presents a general review of some of our selected articles that discuss AI-based telehealth interventions during COVID-19. As Topol[25] describes it, the ultimate prospect for AI in medical technology is to restore the 'valuable bond between patients and physicians—the human touch,' in addition to lowering mistakes and enabling medical staff to spend more quality time.

As a result of the obstacles posed by COVID-19 and the associated lockdowns, many organisations and individuals have adapted robots to help them handle the pandemic's hurdles.[1] While compared with human methods, robotic and autonomous techniques have benefits such as inherent virus immunity and the impossibility of

disease-causing germs passing from human to robot to human. However, the robotics sector still faces many technical challenges. Shen *et al*[1] evaluated over 200 studies discussing robotic systems that emerged or were repurposed during the COVID-19 outbreak to provide insights to academia and businesses. The authors explored the benefits and challenges of using an automated system to combat the COVID-19 pandemic. They discovered that robotic systems are generally effective solutions for most of the issues caused by COVID-19 during surgery, screening, diagnosis, disinfection, telehealth, care, manufacturing, logistics and interpersonal matters unique to pandemic lockdowns.

Ganesh *et al*[26] propose an IoT-based Smart Automated Health Machine, a user-friendly health machine with an interactive GUI for medical needs. It is a virtual health self-screening/check-up/test system that is meant to be an initial point of contact for patient screening to track heart rate, ECG, blood pressure, oxygen saturation and visual acuity. In addition, the system offers essential information and keeps track of various medical concerns and the necessities that need to be adopted. The efforts are part of the United Nations' SDG-3 target.

Chen *et al*[2] analysed the AI's primary scope and contributions in battling COVID-19 from illness detection and diagnostics, pathogenesis and virology, medication and vaccine development, and outbreak and dissemination prediction. The authors also summarise the available data and resources for AI-based COVID-19 studies. Finally, the main obstacles in combating COVID-19 and potential AI directions were highlighted. Chen *et al*[2] discovered that AI still has tremendous potential in this field. The article presents medical and AI scholars with an extensive view of the existing and future applications of AI technologies in the fight against COVID-19 to encourage scholars to continue maximising the benefits of AI and big data in the battle against COVID-19 and future pandemics. Ding *et al*[9] also surveyed various enabling systems and technologies with different application scenarios for tackling the COVID-19 pandemic. Their research focused on three scenarios: wearable devices for observing at-risk and quarantined individuals, assessing nurses and administrative health personnel, and expediting hospital admissions triage; inconspicuous sensing technologies for identifying disease and monitoring patients with relatively modest symptoms whose clinical state could abruptly develop; and telemedicine techniques for remote diagnosis and monitoring of COVID-19 and other relevant illnesses.

Another technique, the internet of medical things (IoMT)-based intelligent healthcare monitoring system, was presented by Dilibal.[11] The primary purpose of this technique is to remotely communicate in digital reality with optimum network throughput and latencies for quick decision-making process management during clinical assessments. Furthermore, the author claims that filtering and compressing raw medical information from real-time video footage is possible with the presented edge enabled IoMT computer architecture system.

Talukder and Haas[27] proposed a sophisticated smartphone-based care system that captures health information using progressive web applications (PWAs), incorporates the data with various health knowledge sources, and employs AI to assist diagnostic evaluation and patient stratification. In addition, the system may make recommendations for actions and treatments and be built with cybersecurity features to tackle data privacy and security issues. The application is built on next-generation internet technologies such as PWA, Web Speech API, Web-Bluetooth, Web-USB and WebRTC and works well with the intelligent hospital concept. However, implementing this system requires buying sophisticated hardware that might be costly to users.

The COVID-19 pandemic has caused an extreme scarcity of personal protective equipment, increasing the risk of infection among medical practitioners.[28] As a result, numerous studies have been conducted to develop enabling systems and techniques that limit disease risk among medical practitioners and other frontline workers. For example, Karanam *et al*[28] designed and developed a contactless patient positioning system using three-dimensional (3D) pose technology that addressed these issues. The authors showed how the device allowed remote scanning of a patient without physical closeness by presenting numerous parts of the system, including automatic calibration, positioning and multiview synthesis methods. While the presented technology allows medical scans to be contactless and more effective, it does not prevent healthcare practitioners from doing patient scans in person if desired in a non-pandemic situation.

Non-AI-based techniques in fighting against COVID-19

This section presents a general review of some of our selected articles that discuss non-AI-based telehealth interventions during the COVID-19 pandemic.

Li *et al*[14] proposed a remote telehealth monitoring technique for COVID-19-infected people in self-isolation that uses a multimodal fusion technique as a practical choice for monitoring self-isolated patients. The authors employed a radar sensor to observe basic activities and respiration and a smart wristband to get details on the patient's blood oxygen saturation and heartbeat. The authors conducted an experimental study with 10 volunteers with an average age of 28. They discovered that the technique is practical and realistic for tracking individuals in self-isolated situations. However, the method requires the purchase of some expensive hardware which might make the technology cost inhibitive to users.

Raj and Srikanth[29] initiated a study and field trial project to assess and evaluate the usefulness and efficacy of an 'assisted telemedicine' approach in tackling the accessibility gaps in the remote primary healthcare environment. Using a collaborative design paradigm, the effort also included creating a blueprint for an Assisted Telehealth app to meet medical consultation needs during and after the COVID-19 pandemic. For the 'assisted telemedicine' concept, a customised application was constructed,

and functionalities were gradually expanded based on observations and comments from different stakeholders. According to their preliminary research, this healthcare delivery paradigm can serve various populations and gain acceptability among multiple stakeholders. Using the capability approach lens, the potential impacts of this action were also investigated. The study encountered difficulties due to a lack of high-speed internet access, especially in remote, rural areas.

Elahraf *et al*[30] presented a service-oriented architecture for dynamically composing and managing tailored treatment plans, assuming an adequate knowledge base and internet service for the underlying systems of caregivers and service providers. The authors created a working prototype to show the practicality of their suggested model and explained the obstacles and problems resulting from putting it into practice. Nevertheless, the need for a sufficient knowledge base and internet services for the underlying systems of caregivers and service providers may not exist in some regions, particularly in distant, rural areas.

Collected telehealth intervention challenges

This section listed and categorised the challenges of the telehealth interventions summarised in online supplemental material, table 2. The reported challenges can be sorted into three categories: (1) technical challenges, (2) non-technical challenges and (3) policy and privacy issues. For more details about the challenges, you may refer to the references provided along with each challenge.

Technical challenges

The primary technical challenges mentioned in the reviewed studies are as follows; the challenges are listed based on their criticality; the top challenges are the most critical ones while the bottom ones are the less critical ones.

- Network issues (especially outside of the healthcare facility).[1 13 26 29–31]
- Difficulty in accurately differentiating between COVID-19 and typical pneumonia or other relevant diseases.[32 33]
- System reliability issues.[1 9 13 26 29]
- Performance and accuracy issues.[1 15 28 34]
- Compatibility issues.[12 35 36]
- Dataset availability issues.[2 9]
- Data imbalances between negative and positive samples.[2]
- A large amount of noisy data and rumours.[2]
- Scarcity of knowledge in the intersection of computer and medical sciences.[2]
- Power consumption.[9]
- Healthcare is highly resistant to change.[13]
- Technical glitches.[29]
- Insufficient bandwidth and resources, as well as effective effort maintenance.[29]
- Scalability, interoperability and auditability issues.[30]

Non-technical challenges

The primary non-technical challenges mentioned in the reviewed studies are as follows; similarly, the challenges are listed based on their criticality; the top challenges are the most critical ones while the bottom ones are the less critical ones.

- Lack of knowledge, technical literacy and skills needed to use virtual medical services (eg, not everybody can use telehealth services and disabled individuals and children need supervision to protect their integrity).[13 15 27 30 35–37]
- Cost associated with developing, subscribing, using or maintaining the system.[1 9 14 26 27 32]
- While telehealth technologies supply high-quality healthcare services, they cannot entirely replace physical treatment.[1 13 15 26 33]
- People's uncertainty about using technology.[15 26 29 33]
- Lack of public or private sector support for advancing medical technology that meets the demands of the populace.[15 29 37]
- Lack of knowledge and awareness about telemedicine and its benefits.[15 29]
- User service misuse.[26]
- Adoption rates are restricted to medical emergencies, which is insufficient.[13]
- Some users (especially those in rural areas) do not use phones.[29]
- It is difficult to have the same doctor(s) for follow-up appointments.[29]

Privacy and policy issues

The primary policy and privacy issues mentioned in the reviewed studies[2 9 11 13 26 29–31 37] are as follows:

- Local laws and stringent regulations could pose a challenge in installing systems, especially in remote areas.[26]
- Data privacy and human rights protection.[9]
- Ethical issues (eg, a clinician may improperly exploit patient data to conduct genetic or biological investigations or dispense medications that violate approved regulations).[37]
- A sound security system is needed to curb user service misuse.[26]

Collected telehealth intervention security issues

Telehealth devices provide aged, physically disabled patients and people in isolation due to COVID-19 with remote care such as surgeries, treatments and diagnoses. In this context, various systemic properties, such as security, must be met for telehealth systems to function correctly. Existing research examines various security incidents involving telehealth systems. This section discusses a comprehensive overview of the most reported telehealth application security issues and the presented remedies.

Marquez *et al*[23] recently performed a systematic mapping investigation to detect, organise and characterise telehealth systems' security vulnerabilities. The authors also

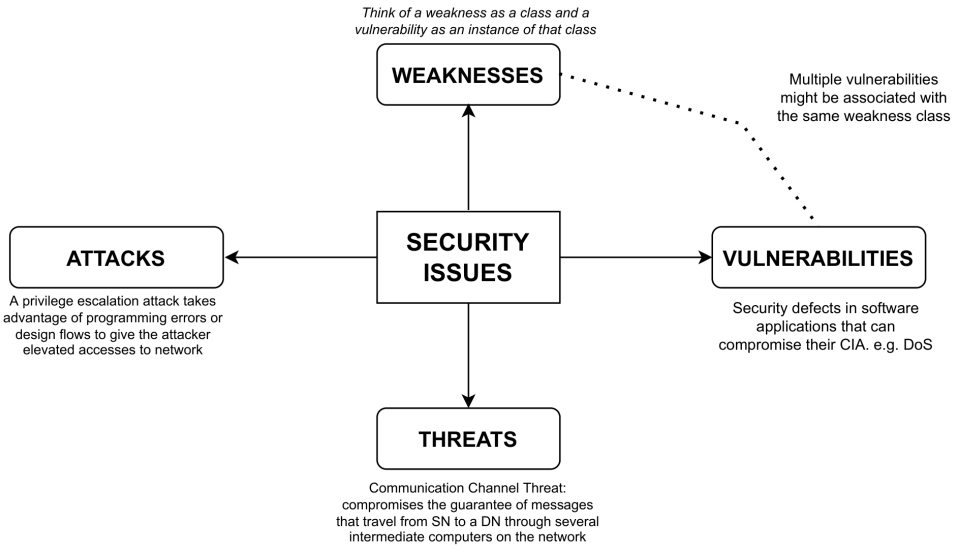

Figure 2 Most common telehealth security issues. SN, source node; DN, destination node; CIA, confidentiality, integrity and availability; DoS, denial of service.

noted how software engineering could aid in developing safe telehealth systems. The findings of their study show that: (1) the most reported security issues fall into four categories (ie, attacks, vulnerabilities, weaknesses and threats); (2) three security mechanisms (ie, detect attacks, stop or mitigate attacks and react to attacks) characterise security solutions and (3) the most related research topics are attributed to insecure data transmission and privacy. The study's findings also suggest that software design, requirements and models are vital areas that need to be focused on to develop secure telehealth systems.

Marquez *et al*[23] also reported that network protocol, such as HTTP (Hypertext Transfer Protocol), is the telehealth component most affected by security issues, followed by watermark, database and access control. Furthermore, in terms of medical supplies affected by security issues, the authors found that the electronic patient record is the most affected supply, followed by medical images, medical robots, wireless medical data and biosensors.

Specifying the most affected components/supplies could help researchers and developers know which components to put more effort into to mitigate reported security issues. Details about the most reported telehealth application security issues and proposed solutions are provided in the following subsections.

Most common telehealth privacy and security issues

Figure 2 illustrates the four most common telehealth security issues discussed in the following paragraphs.

Attacks

According to Marquez *et al*,[23] a privilege escalation attack uses programming faults or design defects to grant a hacker higher network access. The two types of privilege escalation are vertical and horizontal. Vertical privilege escalation needs an attacker to grant themselves greater authority. Horizontal privilege escalation entails the attacker assuming the identity of another user with identical privileges while using the same level of privileges he already has.

Vulnerabilities

Software vulnerabilities (SVs) are security flaws in software applications that can compromise their confidentiality, integrity and availability.[1] Exploiting SVs can harm the operation and reputation of millions of software applications and organisations worldwide and cause significant financial losses. Therefore, it is crucial to remediate critical SVs as soon as possible.

Threats

The guarantee of information travelling from a source point to a destination via numerous intermediate channels on a network is threatened by the communication channel threats.[38] Hussain *et al*[38] and Chryssanthou *et al*[39] describe how social/community threats jeopardise telemedicine system security and name three types of threats: (1) technical, (2) ethical and (3) legal. The details of these threats can be found in Hussain *et al*.[38]

Weaknesses

While a vulnerability is often described in terms of weakness, defining a weakness itself can be difficult. A weakness can be considered a class and a vulnerability as an instance of that class because multiple vulnerabilities might be associated with the same weakness class. A single vulnerability could relate to two or more defects exploited concurrently or sequentially. In this regard, a vulnerability is a collection of one or more instances of weakness.

Most common solutions to telehealth privacy and security issues

As reported by Marquez *et al*[23] and illustrated in figure 3, the three most common telehealth security solutions are

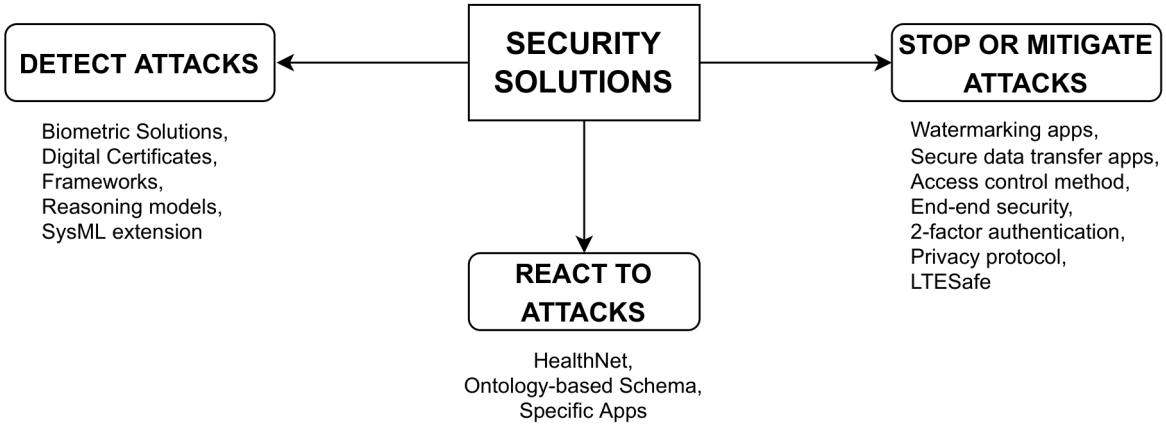

Figure 3 Most common telehealth security solutions.

to: detect attacks (eg, biometric solutions[40]), stop or mitigate attacks (eg, LTESafe,[34] watermarking apps[41]) and react to attacks (eg, healthNet[42]). LTESafe[34] is a cellular-assisted, privacy-preserving COVID-19 contact tracking tool that uses a deep neural network-based feature extractor to translate cellular CSI to a high-dimensional feature space, where the Euclidean distance between points represents device closeness. In this system, user privacy is protected by concealing the physical locations of devices while achieving excellent accuracy.

DISCUSSION

Summary and comparison of the proposed telehealth interventions

Online supplemental material, table 2 summarises and distinguishes the findings of the identified telehealth interventions based on the following criteria; this section discusses and compares the existing telehealth interventions summarised in online supplemental material, table 2.

- Intervention type: denotes the type of application. As discussed in Section 'Methods', there are two main categories. AI-based and non-AI-based systems.
- Scope: specifies the country/area where a particular application was developed or the intended origin of users/study.
- Technology used: denotes the kind of telecommunication or technical systems used to achieve telehealth purposes.
- Advantages/services: specifies the proposed intervention's uses, benefits and contributions in mitigating the COVID-19 pandemic.
- Challenges/limitations: specifies the key issues and constraints of the proposed systems.

As shown in online supplemental material, table 2, 12 out of the 20 (ie, 60%) of our surveyed telehealth interventions are AI-based systems,[1 2 9 11 13 26–28 33 34] while the remaining 8 (40%) are non-AI-based systems.[12 14 15 29 30 35–37] The research covered 11 different countries: the USA,[1 34] the UK,[26] China,[14 28 33] Austria,[32] Bangladesh,[31] Turkey,[11] India,[12 27 29] Ecuador,[15] Pakistan,[30] Qatar,[36] KSA[35] and Brazil.[37] However, some reports[2 9 13] are surveys or reviews which are considered global.

Many telecommunications and technical systems have been used to help achieve remote healthcare. The technologies include but are not limited to mobile and tablet devices, wearable sensor devices, video conferencing tools, online portals, mobile apps/platforms, robotic systems, 3D pose, cameras, IoMT devices, GPS (Global Positioning System) technologies, ultra-wideband, radar sensor devices, smart bracelets, APIs, thermistors, and deep learning and machine learning tools.

A significant number of services and their usage have been reported in this paper. The most studied are patient tracking, triage and monitoring, disease detection and diagnosis, online consultations and prescriptions, disease spread analysis, healthcare accessibility-related challenge mitigation, and COVID-19 symptom checking. In addition, several challenges and limitations have been reported, and details are provided in Section ' Collected Telehealth Intervention Challenges'.

Principal findings

Overall, a total of 27 studies were selected, studied and analysed. The reported telehealth interventions were classified into two main categories: AI-based and non-AI-based interventions; their major contributions to tackling COVID-19 are in the aspects of disease detection and diagnosis, pathogenesis and virology, vaccine and drug development, transmission and epidemic predictions, online patient consultation, tracing, and observation; 28 telehealth intervention challenges/issues have been reported. The collected challenges/issues are classified into three main categories: technical, non-technical, and privacy, and policy issues. Fourteen technical challenges, 10 non-technical challenges and 4 privacy, and policy issues have been reported. Network issues (especially outside of the healthcare facility), system reliability issues, performance, accuracy, and compatibility issues are the most critical technical issues reported in at least 6, 5, 4 and 3 sources of our included studies, respectively. The skills required, hardware/software cost, inability to entirely replace physical treatment, and people's

uncertainty about using the technology are the most critical non-technical challenges reported in at least 7, 6, 5 and 4 sources of our included studies, respectively. Moreover, stringent laws/regulations, ethical issues are some of the policy, and privacy, issues affecting the development of the telehealth interventions reported in the literature. Furthermore, attacks, vulnerabilities, weaknesses and threats are the most common telehealth security issues reported in the literature, while three security mechanisms (ie, detect attacks, stop or mitigate attacks, and react to attacks) characterise the most common telehealth security solutions reported in the literature.

LIMITATIONS AND FUTURE WORK

Most of the selected research papers that introduced novel solutions about telehealth communicate their methodologies and testing procedures poorly or incompletely. They do not elaborate enough on the methods and criteria followed to reach their assumptions or findings. Considerable care and attention have been made to ensure this study's rigour. However, like any chosen research method, it is subject to validity threats. This research focused on a handful of well-known, top-ranking venues (such as *IEEE, ACM, JMIR, BMJ*), which limited our selection of papers and the overall quality of the papers selected. Even though other journals such as PubMed, MEDLINE, Ovid are not as well-known, highly ranked, as those selected for this paper (according to Google Scholar metrics), they still have the potential to offer higher-quality and more relevant research papers. Future work should include more research journals, regardless of how well known they are. Because the topic of this paper is related to the broad field of medicine, articles about telehealth are abundant. Thus, future research should also focus on a specific field in telehealth, such as 'remote monitoring devices' or application-based 'telehealth apps'.

CONCLUSION

This article presents an extensive survey that names and categorises digital health interventions, and their challenges, policy, privacy, and security issues are discussed. The digital health interventions found are mainly classified into AI-based and non-AI-based telehealth interventions. Moreover, the telehealth challenges are categorised into technical challenges (such as network, performance, accuracy, reliability and dataset availability issues) and non-technical challenges (such as cost, uncertainty and user service misuse). In addition, local laws, stringent regulations, ethical issues, data privacy and human rights protection, etc have been reported as policy, privacy and security issues affecting telehealth interventions. The authors of this paper believe that this paper's outcome should motivate scholars to continue to maximise the benefits of these techniques in the fight against COVID-19 and other future diseases. However, the identified challenges, policy, privacy and security issues should be considered when designing and developing future telehealth applications.

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