

An Online Survey of Healthcare Professionals to Understand the Use of Clinical Prediction Models in Practice

Eve Bunni

eve.bunni@liverpool.ac.uk

University of Liverpool

Carol Kingdon

University of Liverpool

Laura Bonnett

University of Liverpool

Millie Brazier

University of Liverpool

Vicky Bradley

University of Liverpool

Abi Merriel

University of Liverpool

Research Article

Keywords: Clinical prediction models (CPMs), digital health tools, healthcare professionals, medical device regulation.

Posted Date: August 6th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10278511/v1>

License:  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

Introduction

Clinical prediction models (CPMs) are increasingly promoted as decision-support tools that can improve patient care. However, their real-world utilisation remains variable, and little is known about the factors influencing their adoption across specialties. This study aimed to explore healthcare professionals' experiences with CPMs, including their perceived usefulness, preferred formats, and the barriers and facilitators to their implementation.

Methods

A cross-sectional survey of healthcare professionals using an online questionnaire using REDCap software was distributed via social media and professional mailing lists, worldwide.

Healthcare professionals from a range of clinical and allied health specialties were invited to complete the online survey. The survey captured demographic data, CPM usage, perceptions of usefulness (via Likert scale), preferred access methods and presentation formats, and included free-text questions for qualitative analysis. Quantitative data were summarised descriptively, and qualitative responses were analysed thematically.

Results

A total of 157 respondents completed the survey, of whom 62% were doctors and 87% were based in the UK. Most respondents (82%) were aware of CPMs, and 71% used them in clinical practice, rating their usefulness at a median of 8 out of 10. The most used models predicted age-related events (e.g. CHA2DS2-VASc, QRISK), while obstetrics and gynaecology (O&G)-specific models were underutilised despite O&G being the most represented specialty. Preferred access methods included web-based tools and mobile applications, and participants favoured percentage or heat map formats for risk presentation. Barriers included poor integration into workflows, limited awareness, regulatory uncertainty, and inconsistent use across teams. Three themes were developed from qualitative free-text responses; why clinicians believe CPMs are clinically useful, how to integrate CPMs into everyday systems and the need for continuous professional education about CPMs.

Conclusions

Healthcare professionals value CPMs but emphasise the need for models that are transparent, user-friendly, and integrated into clinical systems. As AI-driven approaches become more common, concerns around interpretability and inconsistent regulatory classification—such as whether CPMs are considered medical devices—must be addressed. To ensure credibility and usability, future models should adhere to TRIPOD or TRIPOD-AI reporting standards, undergo external validation in independent datasets, and be evaluated for clinical impact. Coordinated efforts by researchers, journals, funders, and regulators are essential to move from model development to meaningful implementation in practice.

Strengths and limitations of this study

- This was a worldwide survey capturing opinion across countries and continents, the online distribution of the survey made this possible.
- The professional mailing lists available to the author were from those working in maternity care and may have influenced numbers of Obstetrics and Gynaecology specialists recruited.
- The list of prediction models in use was not exhaustive but incorporated those used/known most widely. Opportunity to list others was possible in free text format.

Introduction

Over 90% of medical practitioners believe digital health tools are advantageous for their practice according to a survey carried out in America.(1) Predictive modelling uses both mathematical and computational methods to create models that can predict future outcomes. These methods can be applied in many ways in the medical setting including, clinical decision-making and as a prognostic tool. They are however, under-utilised in medical practice namely due to the complex and heterogenous nature of patients, diseases and data sources needed for its construction.(2)

Clinical prediction models in use today are diagnostic (predicting the risk of a specific medical condition) or prognostic (estimating the risk of a future outcome in people with an underlying medical condition). (3) They take multiple contributing risk factors, combining them against the probability of having a condition (diagnostic) or future event (prognostic) and make their overall predictions using statistical regression techniques.

CPMs utilise statistical or machine learning methods to estimate diagnostic or prognostic outcomes based on multiple variables. Common examples include the QRISK score for cardiovascular risk and the CHA2DS2-VASc score for stroke risk. These models are implemented in various formats, such as scoring systems, nomograms, websites, and mobile applications. The best format for a model depends on where and when it is needed. Involving the stakeholder is key in deciding the most favourable approach.(4)

The COVID-19 pandemic catalysed an unprecedented proliferation of CPMs, many of which were later scrutinised for issues around validity and applicability.(5) As the field matures, there is a growing need to understand how and why healthcare professionals use CPMs, the formats they find most accessible, and the challenges they face in implementation.

This study aims to capture a worldwide snapshot of CPM usage among healthcare professionals, with a view to informing future model development and integration strategies. This research aims to understand the models employed, frequency of utilisation and factors influencing their success or failure in real-world clinical scenarios by conducting a comprehensive investigation into the clinical prediction model landscape among healthcare practitioners. By exploring the preferences and experiences of practitioners from diverse medical specialties, we seek to uncover valuable insights that can inform the development, implementation, and improvement of clinical prediction models.

Methods

Figure 1 summarises the methods.

Study Flow Chart

Study design

This is an online, worldwide cross-sectional survey study looking at clinical prediction model use and usability across medical specialties.

Participants and specialty

Eligible participants were practicing healthcare professionals from any specialty or profession, worldwide. This included: doctors, midwives, nurses, physiotherapists, paramedics, physician's assistants, operating department practitioners, pharmacists, with an option for "other healthcare professionals" to be included. Inactive or retired healthcare professionals were excluded from the study.

Sample size and rationale

As our aim was to gather opinions and usage of CPMs. A pragmatic approach was used to determine sample size, rather than performing a sample size calculation. We chose a 200-participant target sample size from professionals across diverse specialties worldwide. this is in line with existing quantitative instrument validation studies, where around 90% had a sample sizes of > 100 along but very few studies had sample sizes > 1000 (14% and 7% respectively).(6, 7) Given this was an exploratory survey study, not for hypothesis testing, a sample size of 200 was felt to would gather sufficient data on usage and opinion of CPMs across medical specialties, and is congruent with similar studies.(8) The study remained open for 8 weeks.

Recruitment

A convenience sampling strategy was employed.(9) Participants were recruited online through social media: Facebook, X (formerly Twitter) and Instagram.(10) Emails were sent to the health care workers on our study mailing lists with over 100 members. The Options study is developing a prediction model for emergency caesarean births in first pregnancies, and the findings of this survey will inform the presentation of the prediction model.

A hyperlink and QR code were provided on the advertisement, directing participants to the survey.

Survey

The online survey was produced and disseminated using REDCap software.(11) CAPTCHA software was used to enhance online security. After providing information and obtaining consent the survey addressed demographic questions, clinical prediction model use, factors influencing usage and success, evaluation of clinical prediction models with the opportunity for additional comments (supplementary file 1).

Data analysis

Likert scale analysis assessed perceived usefulness and frequency of usage of prediction models (scores of 1–10). Descriptive statistics were calculated for any quantitative data that was captured e.g. frequencies, percentages, median Likert scores. Qualitative, free-text responses were thematically analysed using Braun and Clarke’s six-stage approach to identify common themes related to the barriers, facilitators and implementation considerations to use of prediction models.(12)

Patient and Public Involvement

Patients or the public were not involved in the design, conduct, reporting, or dissemination plans of our research as the study participants were healthcare professionals.

Results

Respondent Characteristics

157 healthcare professionals took part in the survey. The professional spread included 62% doctors, 17% nurses, 15% midwives, 7% other healthcare professionals and 3% paramedics. Those that deemed themselves to be in the “other” category comprised of: advanced clinical practitioners, occupational therapist, clinical scientist, biomedical scientist, emergency medical technician, and a dietitian. 87% of respondents were from the UK, with the remaining 13% of recruits from a spread of countries worldwide including; India, South Africa, Malawi, Uganda, Australia, Brunei, and USA.

Awareness and Use of Clinical Prediction Models

82% of healthcare professionals were aware of clinical prediction models, 71% used them in their practice. 2% of respondents were unsure what a clinical prediction model was.

Healthcare professionals deemed clinical prediction models to be very useful in clinical practice, scoring a median of 8/10 on a Likert scale (1 not useful at all to 10 being extremely useful). Frequency of use varied, with over 60% reporting weekly or daily usage.

Specialty Representation and Model Use

Responses to the survey were spread across medical specialties, the top three medical specialties that responded to the survey were Obstetrics and Gynaecology (35%), Other (19%), and GP (18%). Additionally, a significant number of responses were from medicine (10%) and paediatrics (7%). The

remaining 11% of respondents were distributed across a wide range of specialties including acute medicine, ITU, anaesthetics, surgery, psychiatry, public health, oncology, medical microbiology, and pharmacology. Those deeming themselves to work in the “other” category included neurology, radiology, haematology, research, clinical biochemistry, emergency medicine, and fetal medicine.

Despite the most frequent responders being from obstetrics and gynaecology, commonly used CPMs were those predicting age-related morbidity, such as the CHA₂DS₂-VASc (41%), CURB-65 (35%), QRISK (31%), HAS-BLED (30%), and FRAX (24%) scores. Indeed, 16 O&G prediction models were listed in the question asking, “which of the following prediction models do you use?” However, none of these came in the top 5 most used models.

See Table 1 for the list of clinical prediction models provided in the survey and an explanation of the type and dominant specialty for each CPM.

Table 1
Prediction models listed in survey, their type and specialty.

Prediction Model Name	Prediction Model Type	Specialty
CHA2DS2-VASc Score	Stroke risk for atrial fibrillation	Cardiology
CURB-65 Score	Mortality community acquired pneumonia and inpatient/outpatient treatment	Respiratory/AED
QRISK (1,2 or 3)	Risk of myocardial infarction/stroke over 10 years	GP/Cardiology
HAS-BLED Score	Risk of major bleeding on anticoagulation for atrial fibrillation	Cardiology/Haematology
FRAX	10 year fracture risk	Orthopaedics
QUIPP	Pre-term labour tool.	Obstetrics
FMF: Pre-eclampsia	Risk of pre-eclampsia (split into weeks)	Obstetrics
FMF: Fetal growth restriction	Risk fetal growth restriction	Obstetrics
TNM Staging System	Tumour Node Metastases staging for cancer	Oncology
FMF:Preterm birth - history	Pre-term labour risk acc. to history	Obstetrics
FMF: Preterm birth - cervix	Pre-term labour risk acc. to cervix	Obstetrics
FMF: Trisomies	Trisomies 13,18,21 risk	Obstetrics
Fetal Medicine Foundation (FMF) risk prediction models:	Details above	Obstetrics
FMF:SGA	Risk for SGA < 10th centile	Obstetrics
FMF: Stillbirth	Stillbirth > 24 weeks risk	Obstetrics
RMI (Risk of Malignancy Index)	Ovarian Cancer risk score	Gynae oncology
SOFA	ICU mortality	ICU

Prediction Model Name	Prediction Model Type	Specialty
GRACE Score	6-month mortality for acute coronary syndrome	Cardiology
Duke Criteria	Diagnostic criteria, infective endocarditis	ID/cardiology/medicine
FMF: Fetal macrosomia	Risk Macrosomia	Obstetrics
FMF: Gestational diabetes	Gestational diabetes risk	Obstetrics
FMF: Miscarriage	Miscarriage risk < 24 weeks	Obstetrics
POSSUM	Surgical risk prediction	General/colorectal/oesophagogastric/vascular surgery
APACHE II	ICU mortality	ICU
TIMI Risk Score	Unstable angina and non-ST elevation myocardial infarction	Cardiology, AED
BODE Index	Survival rate of those with COPD	Medicine/Resp
Framingham Risk Score	10 Yr risk of myocardial infarction	Cardiology, GP
PREDICT Breast Cancer Model	Different treatments for invasive breast cancer, improve survival rates	Oncology
ATRIA Bleeding Risk Score	Bleeding risk score if on warfarin	Cardiology
Flamm/Grobman VBAC Calculator	VBAC Calc	Obstetrics
PRISM	Risk of pancreatic cancer	Oncology
PIERS Model	Pre-eclampsia risk assessment of outcomes for inpatients	Obstetrics

The clinical prediction models participants were most aware of were CURB-65 (54%), CHA2DS2-VASc Score (53%), the TNM staging system (53%), QRISK (47%), and HAS-BLED Score (43%).

See Fig. 2 for the full list and variety of prediction models used by the respondents.

Preferred Access and Presentation

Clinical prediction models are accessed most frequently via a website (47%) but are also often accessed by mobile app (33%). 35% of healthcare professionals recorded that they accessed clinical prediction models via both website and mobile app. The format least in use was paper (12%). 16% of healthcare professionals use other formats. These included the clinical prediction model being embedded into the clinical system and some people mentally adding up the score in their head.

When asked about factors that would influence a healthcare professional's usage of a clinical prediction model, healthcare professionals felt that it was very important to present the evidence underpinning the prediction model (median Likert score of 8/10). A similar amount of healthcare professionals felt that accessing the prediction model via a website or mobile app was best (68% and 62% respectively). The top 2 ways to present the results of the prediction model were percentage risk or a heat map (35 and 31% respectively). Although, 27% felt a mixture of icons was the best way to present the results. There was a relatively similar spread between bar chart, sliding scale, pie chart and icon array (24, 23, 21, 20% respectively).

Healthcare professionals felt that clinical prediction models should mostly be used by clinical staff (56%). 43% felt that both clinicians and patients should have use of the prediction model. Only 1% felt it should be used only by patients.

Facilitators and Barriers

When asked what encourages the healthcare professional to use the clinical prediction model, the top five reasons were:

1. Ease of use (76%).
2. Ease of access (74%).
3. To use as a decision aid (70%).
4. There is high quality evidence of its usefulness (67%).
5. Guidelines (63%).

When asked what hinders their use of a clinical prediction model, the top five reasons were:

1. Whether they are in line with current practice (56%).
2. Their accessibility (53%).
3. Their lack of consistent use throughout their specialty (44%).
4. The amount of data to input (41%).
5. Internet access (33%).

In addition to the quantitative survey responses, all participants provided at least one free-text comment. Thematic analysis of these qualitative responses adds more in-depth insights into healthcare professionals' experiences with CPMs, perceived usefulness, preferred formats, and the barriers and facilitators to their implementation. We report three themes:

1. Why clinicians believe CPMs are clinically useful
2. How to integrate CPMs into everyday systems
3. Need for continuous professional education about CPMs

Theme 1: Why clinicians believe CPMs are clinically useful

Participants suggested a key driver to using CPM's is that they are easy to use and interpret, can enhance patient-doctor communication, prepare patients for likely outcomes and justify decision-making, in time limited clinical encounters. Most participants believed they were a useful tool to stratify and assess risk to inform treatment and management strategies. Easy visuals made them particularly appealing. Some participants stressed they sit alongside clinical opinion as an aid, or a guide, because they will not apply to every patient. Participants said they were more likely to use them if the evidence base was robust, valuing the power this gave to their decision-making. Participants said they would be more persuaded with 'high quality evidence demonstrating improvement in clinical outcomes' and a 'robust evidence base used widely in both primary and secondary care'. Some participants mentioned wanting more scientific evidence backing for the models before they would use them. Participants were most likely to use if the CPM was recommended for use in local or national guidelines and they were taught to use in medical school.

A lot of the clinical prediction models that are used, at least in ED, are established models with decades of evidence and use cases and therefore are inherently baked into practice from being taught at medical school to being used on the frontline.ID81

Theme 2: How to integrate CPMs into the frontline

Having links to tools that are used by ambulance services would encourage its use, such as JRCALC guidelines App.ID69

Ease of use was the key driver to uptake across medical specialities. Participants also said accessibility improves prediction model use. Participants routinely use apps on their phone during clinical care, with integration into existing apps seen as a facilitator to use. Integrating CPMs into electronic patient records "documentation software" was viewed as a vital way of integrating CPMS into usual care. Multiple participants mentioned the models being more useful if they were 'integrated onto software for documentation such as 'EMIS' or having 'quick accessibility and automatic updates.' There were also calls for standardisation, across CPMs, use of the same CPM within specialties and across place. Health system adoption was seen as key to 'standardised use across the region' or if they were 'adopted universally at health service level' or 'if they were linked with trust guidelines and indicated appropriate actions to take based on trust policy'. At the same time, they need to be adaptive to local hospital guidelines and practice, to reflect available treatment options. The following quote illustrates the importance of integration into the IT system and the healthcare system.

I think having risk prediction models integrated within IT is vital. In our health board you cannot send a patient with suspected PE to the same day emergency care without a PERC score for example.ID133

Theme 3: Need for continuous professional education about CPMs

I think there is a lack of understanding among GPs about which prediction rules are correct for which populations. eg centor criteria is validated in adults not children I think, but see colleagues using this so clarity/education useful here.ID120

Continuous professional education was reported as an important implementation consideration for effective use of CPMs. Participants' comments encapsulated a need for improved education on prediction models to ensure they are used in the context they were designed in and the population the model was validated for. There was also recognition that CPMs are a new and rapidly evolving field, and there is a need to keep pace with the latest technological developments, including the role of AI.

Developing AI clinical prediction tools are an important component of evolving clinical prediction tools.ID13

Discussion

Main Findings

This worldwide survey study provides insights into the use of clinical prediction models (CPMs) in routine practice, highlighting both their perceived utility and the multifaceted barriers that impede their integration into clinical workflows. Clinical decision making routinely involves balancing risks or probabilities and prediction models can facilitate this.(13)

Most respondents reported familiarity with CPMs and considered them useful tools for supporting decision-making. Yet, even among specialties with established models—such as obstetrics and gynaecology—there appears to be a gap between availability and real-world use, suggesting issues in adoption, accessibility, or trust in the tools.

The most widely used clinical prediction models were those which predicted or guided the management of age-related events (CHA2DS2-VASc Score, CURB-65 Score, and QRISK.) The literature supports their widespread use within their specialty and some are endorsed for use by NICE for example; QRISK3.(14–16) There are prediction models in every field, but evidence suggests that there is a gap between their production and evidence about their impact and performance, thus stalling their widespread use within the clinical setting.(17)

Practically, healthcare professionals showed a preference for access to be via a website or mobile app. Accessibility was also a common theme brought up in the free-text responses collected from participants. With healthcare professionals being more computer-literate and seeing websites and apps

that are well-designed and efficient there is increasing feeling that the healthcare service needs to catch up.(18) Having a website or mobile app that has very few barriers to access and a prediction model that is straightforward to use would enhance its widespread use and improve efficiency within the time-limited clinical consultation that healthcare professionals and patients face.(1)

Healthcare professionals expressed that displaying the score of a prediction model as a percentage risk or heat map would be most effective for them, although it was also popular to display a mixture of icons when communicating the score during a clinical scenario. Displaying data in a digestible and understandable format is important not only for the clinician, but the patients themselves. Percentages and heat maps are unique and different ways of expressing a prediction score. Evidence suggests that preferences for how risk or probability is communicated vary widely amongst the population and therefore multiple representations of the same score have been suggested to potentially tackle this issue.(19)

Free text responses from the survey revealed some valuable insights into healthcare professional's main motivators and barriers to their use of clinical prediction models. Recurrent themes emerged of "embedding" prediction models into local policy or national guidelines, highlighting that a potential barrier to implementation of clinical prediction models could be that clinicians are not made aware that they exist and lack of widespread use amongst colleagues results in them being underutilised in clinical practice.(20)

In summary, the findings reinforce the need for CPMs to be developed with usability in mind, embedded within electronic health record systems, supported by robust evidence, and ideally endorsed by national or local guidelines. Accessibility through mobile or web-based platforms and the presentation of results in understandable formats—such as percentage risks or heat maps—were frequently cited as critical to effective use.

Interpretation in Context of Broader Literature

This survey study supports existing literature that suggests that prediction models are widely used and deemed important to healthcare professionals.(21) Indeed, this study aligns with broader calls from the research and clinical communities for tools that meaningfully address clinical priorities. The James Lind Alliance (JLA), which brings together patients, carers, and clinicians to identify unanswered questions of importance, has consistently highlighted the need for better decision-support in clinical practice.(22) CPMs, when appropriately developed and applied, can respond directly to this priority by informing discussions around risk and shared decision-making.

The survey also repeatedly highlights the importance that an accessible, easy to use clinical prediction model would encourage its use supporting existing guidance on clinical prediction model development. (4) The recent surge in the development of machine learning (ML) and artificial intelligence (AI)-based prediction models has further shaped the research landscape. These models promise powerful capabilities for pattern recognition and predictive accuracy.(23) However, the literature increasingly

points to concerns around their “black box” nature, lack of interpretability, and often poor adherence to reporting and validation standards.(24) Transparency remains a core limitation, with many models insufficiently described in published studies and rarely externally validated.(25) This has led to skepticism among clinicians and limited real-world implementation despite a growing volume of publications.

Furthermore, regulatory ambiguity presents a significant challenge. The UK’s Medicines and Healthcare products Regulatory Agency (MHRA) has issued guidance on software as a medical device (SaMD), yet there remains a lack of clarity over whether all CPMs should fall within the remit of medical device regulation.(26) Mixed messages regarding whether a CPM constitutes a device, depending on its intended use or level of automation, has left researchers and developers uncertain about their obligations.(27) This ambiguity is compounded by inconsistent advice across institutional research ethics committees, NHS research governance bodies, and higher education institutions, is hindering innovation and deployment. A unified, transparent regulatory framework is urgently needed.

Strengths and limitations

This survey study shed light on the opinions of healthcare professionals on clinical prediction models across all medical specialties and successfully recruited participants spanning across a diverse range of clinical specialties, capturing the widespread opinion of those working in healthcare. The survey was not confined to the UK, although it’s acknowledged that the majority of the participants were from the UK. Nevertheless, opinion was captured from those in different countries and continents. Launching the survey through social media and colleagues abroad made this a possibility.

The most highly represented specialty was O&G which is most likely a result of this study being part of a wider body of research called “Options” and therefore recruitment of professionals via our mailing lists and social media accounts were most frequently working in maternity care.(28)

Implications for practice and research

Healthcare professionals wish for a personalised approach in their clinical practice to guide or predict clinical care or outcomes.(20) This study underscores the need for rigorous standards in the development and implementation of CPMs. Statistically robust models must be built on high-quality data and follow established reporting frameworks such as the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) guidelines and the more recent TRIPOD-AI extension for AI-based models.(29) Adherence to these guidelines not only enhances reproducibility and comparability but also facilitates appraisal by clinicians, reviewers, and regulators.

However, good reporting alone is insufficient. Prediction models must be validated in independent datasets that reflect real-world clinical populations.(30) Without external validation, the generalisability and clinical value of a model remain uncertain. Furthermore, models should be presented in formats that

are not only statistically sound but clinically meaningful—supporting interpretability, patient engagement, and timely decision-making.(4)

There is also a need for robust evaluation of CPMs beyond model development and validation. Impact studies—evaluating how CPMs influence clinical behaviour, patient outcomes, workflow efficiency, and health system metrics—are currently underrepresented in the literature.(3) For CPMs to be trusted and adopted, evidence of clinical utility is essential. This requires dedicated funding and editorial commitment. Journals should consistently require TRIPOD (or TRIPOD-AI) compliance for submitted manuscripts, and funders should recognise the critical importance of implementation science and model evaluation studies—not just model development.

Finally, regulatory bodies such as the MHRA, as well as NHS ethics committees and university research governance departments, must offer clear, consistent guidance on the classification of prediction models as medical devices. A harmonised approach would streamline the development-to-implementation pipeline and reduce unnecessary barriers for researchers seeking to translate models into practice.

Conclusion

Clinical prediction models are widely regarded by healthcare professionals as valuable tools for supporting clinical decision-making, yet their adoption into routine practice remains inconsistent. This study highlights key enablers—such as ease of access, integration with clinical workflows, and meaningful presentation of results—as well as persistent barriers, including regulatory ambiguity, lack of validation, and usability concerns.

As the field increasingly embraces complex models built using machine learning and artificial intelligence, ensuring transparency and interpretability becomes even more critical. Adherence to reporting standards such as TRIPOD and TRIPOD-AI, alongside robust external validation, is essential to building trust and facilitating implementation.

Greater institutional clarity is also needed. Regulatory bodies, research ethics committees, and funding organisations must provide consistent guidance on the classification and oversight of prediction models. Journals and peer reviewers have a key role in enforcing methodological and reporting standards, and funders must recognise the value of research that evaluates the real-world impact of these tools—not just their theoretical performance.

To fully realise the potential of prediction models in clinical care, future efforts must prioritise usability, transparency, and evidence of clinical utility. Only then can such tools meaningfully contribute to improved patient outcomes and more efficient, evidence-informed healthcare delivery.

Abbreviations

CPM
Clinical Prediction Model
O&G
Obstetrics and gynaecology
TRIPOD/ TRIPOD
AI–Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis +/-
Artificial Intelligence
NICE
National institute for Health and Care Excellence
JLA
James Lind Alliance
ML
Machine learning
MHRA
Medicines and Healthcare products Regulatory Agency
SaMD
Software as a medical device
NHS
National Health Service

Declarations

Ethical Statement

The protocol was approved by University of Liverpool, Institute of Life Course and Medical Sciences Research Ethics Committee (14353, on 22/07/2024) in accordance with the University of Liverpool research ethics guidelines and regulations.

Consent to participate

Informed consent obtained from each participant at the beginning of the REDCap survey (supplementary file 1).

Consent to publish

Not applicable, no identifiable personal data or images present.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing Interests

The authors declare that they have no competing interests.

Funding

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

AM, NIHR Advanced Fellow, (NIHR302530) is funded by the NIHR for this research project. The views expressed in this publication are those of the author(s) and not necessarily those of the NIHR, NHS or the UK Department of Health and Social Care.

For the purpose of Open Access, the author has applied a CC by public copyright licence to any Author Accepted Manuscript version arising from this submission.

Author's Contributions

EB is the lead author and guarantor of the manuscript and affirms that the manuscript is an honest, accurate, and transparent account of the study being reported and that no important aspects of the study have been omitted. EB produced the protocol and study materials. EB produced the survey and transposed it onto REDCap. EB disseminated the survey, extrapolated the data from REDCap and analysed the quantitative and qualitative data. CK, LB and AM contributed to the production of the protocol, study materials and survey. MB and CK thematically analysed the qualitative data from the survey. VB contributed to the dissemination, advertisement and recruitment of participants. EB, LB, CK and AM wrote the first draft of the manuscript. All authors read and approved the final manuscript.

Acknowledgements

Not applicable.

References

1. Henry TA. 5 insights into how physicians view, use digital health tools. 2024.
2. Toma M, Wei CO. Predictive Modeling in Medicine. Encyclopedia. 2023;3(2):590–601.
3. Prognosis Research in Healthcare. In: Riley RD, van der Windt D, Croft P, Moons KGM, editors. Concepts, Methods, and Impact. Oxford University Press; 2019. 01 Feb 2019.
4. Bonnett LJ, Snell KIE, Collins GS, Riley RD. Guide to presenting clinical prediction models for use in clinical settings. BMJ. 2019;365:l737.
5. Nixon K, Jindal S, Parker F, Marshall M, Reich NG, Ghobadi K, et al. Real-time COVID-19 forecasting: challenges and opportunities of model performance and translation. Lancet Digit Health. 2022;4(10):e699–701.
6. White M. Sample size in quantitative instrument validation studies: A systematic review of articles published in Scopus, 2021. Heliyon. 2022;8(12).

7. Anthoine E, Moret L, Regnault A, Sébille V, Hardouin JB. Sample size used to validate a scale: a review of publications on newly-developed patient reported outcomes measures. *Health Qual Life Outcomes*. 2014;12:176.
8. Daniel J. *Sampling Essentials: Practical Guidelines for Making Sampling Choices*. Thousand Oaks, California: SAGE Publications, Inc.; 2012. Available from: <https://methods.sagepub.com/book/mono/sampling-essentials/toc>
9. Golzar J, Tajik O, Noor S. Convenience Sampl. 2022;1:72–7.
10. Ali SH, Foreman J, Capasso A, Jones AM, Tozan Y, DiClemente RJ. Social media as a recruitment platform for a nationwide online survey of COVID-19 knowledge, beliefs, and practices in the United States: methodology and feasibility analysis. *BMC Med Res Methodol*. 2020;20(1):116.
11. Garcia KKS, Abrahão AA. Research Development Using REDCap Software. *Healthc Inf Res*. 2021;27(4):341–9.
12. Braun V, Clarke V. Using thematic analysis in psychology. *Qualitative Res Psychol*. 2006;3(2):77–101.
13. van Smeden M, Reitsma JB, Riley RD, Collins GS, Moons KG. Clinical prediction models: diagnosis versus prognosis. *J Clin Epidemiol*. 2021;132:142–5.
14. Zheng JY, Li DT, Qiu YG, Huang YX, Xu ZM, Zhao L, et al. CHA2DS2-VASc score as a prognostic indicator in patients with atrial fibrillation undergoing coronary stenting. *Turk J Med Sci*. 2022;52(4):1103–10.
15. Brabrand M, Henriksen DP. CURB-65 Score is Equal to NEWS for Identifying Mortality Risk of Pneumonia Patients: An Observational Study. *Lung*. 2018;196(3):359–61.
16. Nicecomms, Scenario. CVD risk assessment | Management | CVD risk assessment and management | CKS | NICE: @NICEcomms; 2025 [Available from: <https://cks.nice.org.uk/topics/cvd-risk-assessment-management/management/cvd-risk-assessment/>]
17. Kleinrouweler CE, Cheong-See FM, Collins GS, Kwee A, Thangaratinam S, Khan KS, et al. Prognostic models in obstetrics: available, but far from applicable. *Am J Obstet Gynecol*. 2016;214(1):79–e9036.
18. Gulland A. Doctors developing apps to try to modernise the NHS. *BMJ*. 2018;360:k685.
19. Spiegelhalter D. Communicating Risk. *Risk&Regulation*. 2009(Winter):8–9.
20. Hunt A, Bonnett L, Heron J, Lawton M, Clayton G, Smith G et al. Systematic Review of Clinical Prediction Models for the Risk of Emergency Caesarean Births. *BJOG: An International Journal of Obstetrics & Gynaecology*.n/a(n/a).
21. Strandberg R, Jepsen P, Hagström H. Developing and validating clinical prediction models in hepatology – An overview for clinicians. *Journal of Hepatology*. 2024;81(1):149 – 62.
22. James Lind Alliance. Priority Setting Partnerships [Available from: <https://www.jla.nihr.ac.uk/priority-setting-partnerships>]

23. Sarker M, Revolutionizing, Healthcare. The Role of Machine Learning in the Health Sector. <https://jaigsorg/index.php/JAIGS>. 2024.
24. Chen JH, Asch SM. Machine Learning and Prediction in Medicine - Beyond the Peak of Inflated Expectations. *N Engl J Med*. 2017;376(26):2507–9.
25. Wynants L, Van Calster B, Collins GS, Riley RD, Heinze G, Schuit E, et al. Prediction models for diagnosis and prognosis of covid-19: systematic review and critical appraisal. *BMJ*. 2020;369:m1328.
26. MHRA Software flowchart. In: MHRA, editor. 2014.
27. Hassan N, Slight R, Morgan G, Bates DW, Gallier S, Sapey E, et al. Road map for clinicians to develop and evaluate AI predictive models to inform clinical decision-making. *BMJ Health Care Inf*. 2023;30(1):e100784.
28. Sciences IoLCaM. The Options Study University of Liverpool Website2024 [Available from: <https://www.liverpool.ac.uk/life-course-and-medical-sciences/about/womens-and-childrens-health/options/>]
29. Collins GS, Moons KGM, Dhiman P, Riley RD, Beam AL, Van Calster B, et al. TRIPOD + AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. *BMJ*. 2024;385:e078378.
30. Omar R. Clinical Prediction Models: A Practical Approach to Development, Validation and Updating by STEYERBERG. *E W Biometrics*. 2010;66(2):661–2.

Figures

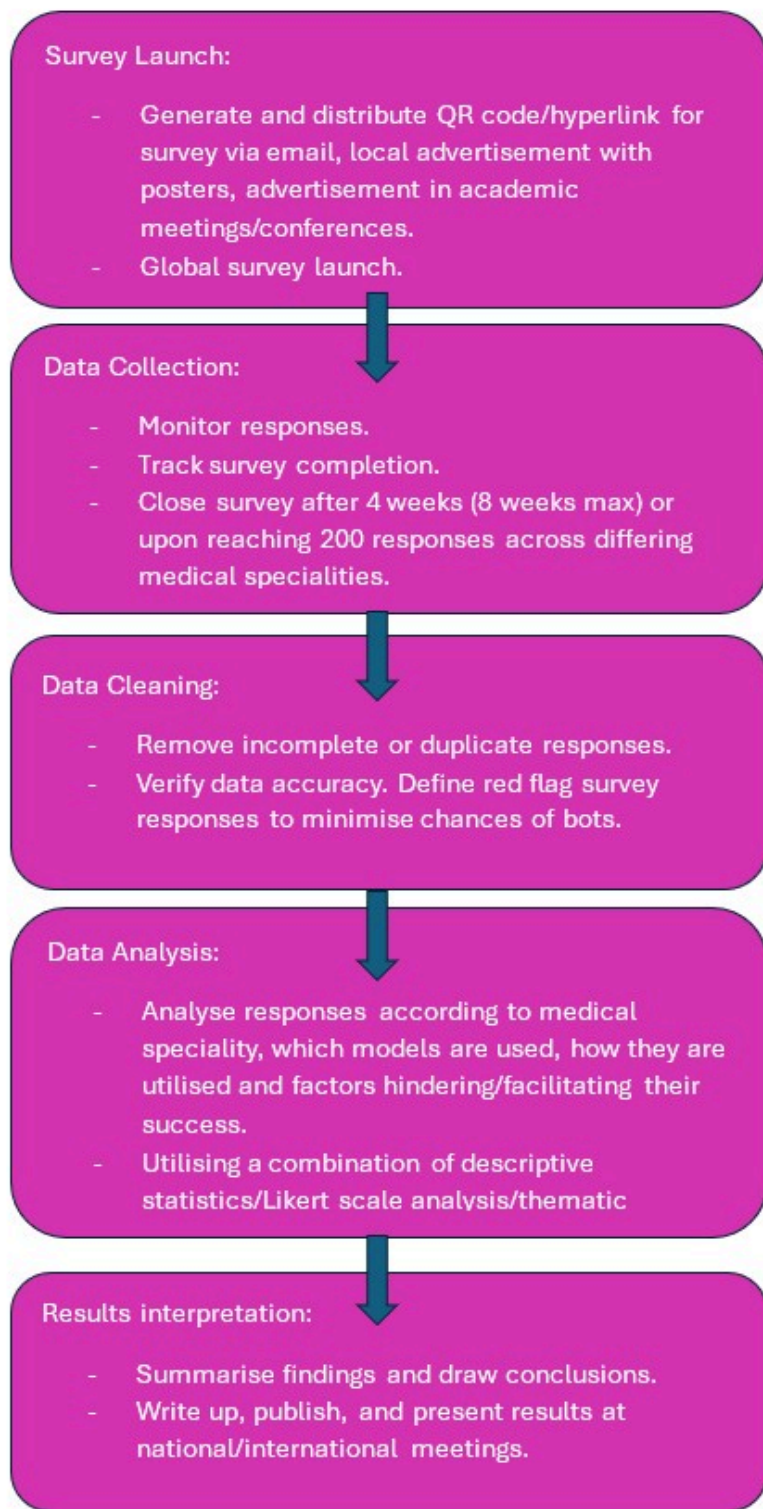


Figure 1

Study flow chart. Outline of study and methodology.

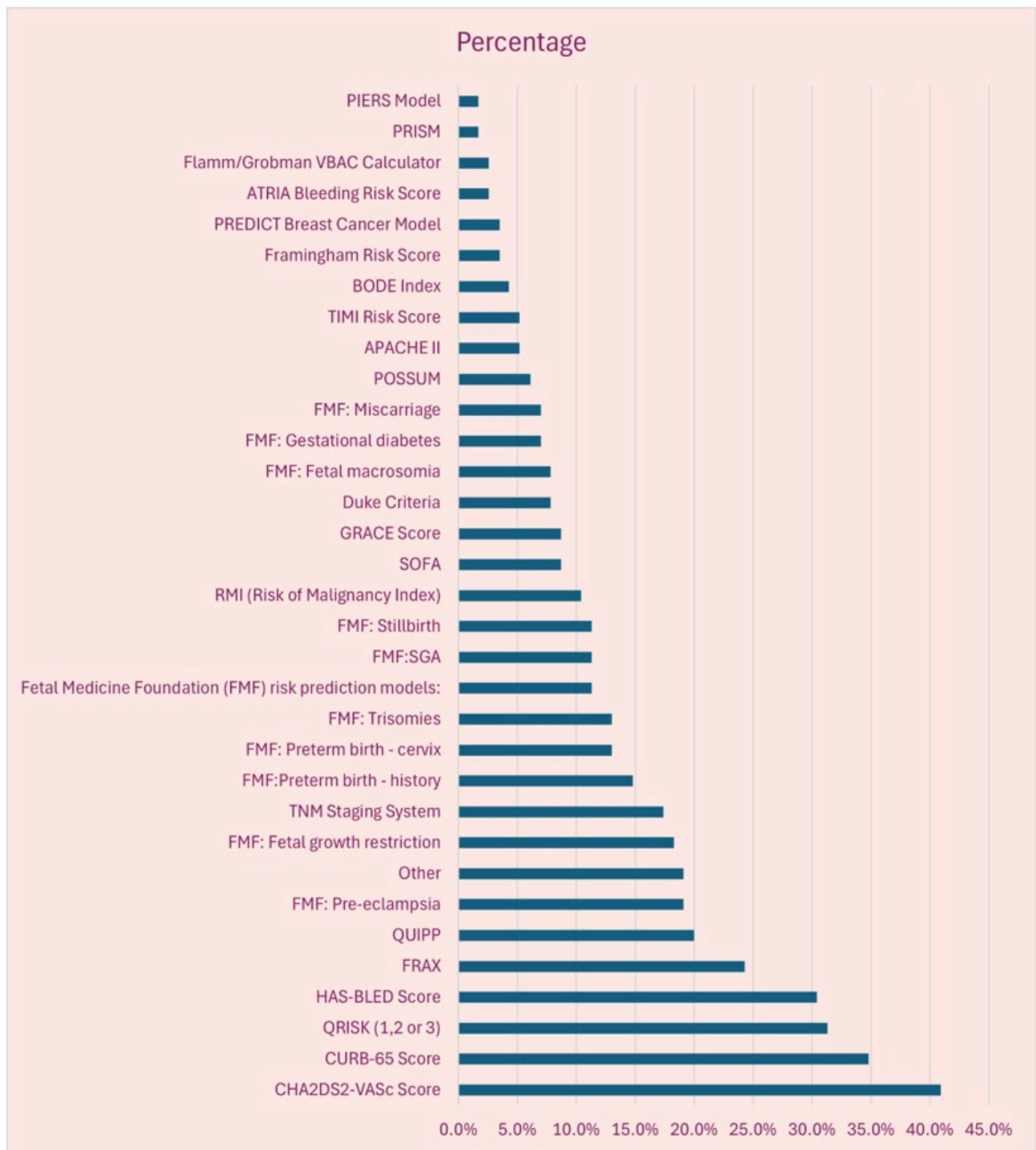


Figure 2

Clinical prediction models currently in use. Responses in order of usage to the survey question “Which of the following prediction models, do you use in your clinical practice?”

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SUPPFI1.doc](#)
- [SUPPFI2.doc](#)
- [Suppfile1REDCapSurvey020724.pdf](#)