Machine learning methods for automatic pain assessment using facial expression information

Protocol for a systematic review and meta-analysis

Dianbo Liu, PhD\textsuperscript{a}, Dan Cheng, MD, PhD\textsuperscript{b,c}, Timothy T. Houle, PhD\textsuperscript{b}, Lucy Chen, MD\textsuperscript{b}, Wei Zhang, MD, PhD\textsuperscript{c,*}, Hao Deng, MD, MPH\textsuperscript{b,*}

Abstract

Introduction: Prediction of pain using machine learning algorithms is an emerging field in both computer science and clinical medicine. Several machine algorithms were developed and validated in recent years. However, the majority of studies in this topic were published on bioinformatics or computer science journals instead of medical journals. This tendency and preference led to a gap of knowledge and acknowledgment between computer scientists who invent the algorithm and medical researchers who may use the algorithms in practice. As a consequence, some of these prediction papers did not discuss the clinical utility aspects and were causally reported without following related professional guidelines (e.g., TRIPOD statement). The aim of this protocol is to systematically summarize the current evidences about performance and utility of different machine learning methods used for automatic pain assessments based on human facial expression. In addition, this study is aimed to demonstrate and fill the knowledge gap to promote interdisciplinary collaboration.

Methods and analysis: We will search all English language literature in the following electronic databases: PubMed, Web of Science and IEEE Xplore. A systematic review and meta-analysis summarizing the accuracy, interpretability, generalizability, and computational efficiency of machine learning methods will be conducted. Subgroup analyses by machine learning method types will be conducted.

Timeline: The formal meta-analysis will start on Jan 15, 2019 and expected to finish by April 15, 2019.

Ethics and dissemination: Ethical approval will be exempted or will not be required because the data collected and analyzed in this meta-analysis will not be on an individual level. The results will be disseminated in the form of an official publication in a peer-reviewed journal and/or presentation at relevant conferences.

Registration: PROSPERO CRD42018103059.

Abbreviations: AUC ROC = area under curve for receiver operating characteristic curve, MSE = Mean Square Error, OPI = Observer Pain Intensity, SRDR = Systematic Review Data Repository, VAS = Visual Analog Scale.

Keywords: accuracy, machine learning, neural networks, pain, prediction

Our systematic review and meta-analysis will provide the first quantitative and systematic summary of current state of research of automatic pain estimating algorithms regarding their performance and clinical utility.

The results of this meta-analysis will help clinicians and researchers understand the strength and limitations of both current score-based pain assessment system and computer algorithms in development for automatically predicting clinical pain. It will also provide insights for researchers to improve the accuracy and generalizability of automatic pain assessment algorithms.

The main limitation of our study is that most of these studies were led and conducted by computer scientists instead of medical researchers. Their methods were mathematically sound; however, many clinical factors (e.g., psychosocial factors, different pain neurological mechanisms) were not considered and the reporting of their results was not standardized for medical meta-analysis.

This work was supported by the National Natural Science Foundation of China, with the funding reference number of 81571082. This project was also supported by departmental funds of Department of Anesthesia of The First Affiliated Hospital of Zhengzhou University.

Ethical approval will be exempted or will not be required because the data collected and analyzed in this meta-analysis will not be on an individual level. The results will be disseminated in the form of an official publication in a peer-reviewed journal and/or presentation at relevant conferences.

The authors have no conflicts of interest to disclose.

\textsuperscript{a} Computer Science and Artificial Intelligence Laboratory, MIT, Cambridge, \textsuperscript{b} Massachusetts General Hospital, Boston, MA, \textsuperscript{c} The First Affiliated Hospital of Zhengzhou University, Henan, PR China.

Copyright © 2018 The Author(s). Published by Wolters Kluwer Health, Inc.

This is an open access article distributed under the Creative Commons Attribution License 4.0 (CCBY), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Medicine (2018) 97:49(e13421)
Received: 31 October 2018 / Accepted: 2 November 2018
http://dx.doi.org/10.1097/MD.0000000000013421
1. Introduction

Pain is an internal and private experience with complicated neuro-psychosocial mechanisms. Patient’s self-report remains to be the golden standard for pain assessment in both medical and computational field, among which Numeric Rating Scale (NRS) and Visual Analog Scale (VAS) are the 2 most widely used quantitative pain scales in clinical settings. However, these 2 measures are severely subjected to reporting bias due to the nature of self-report and are influenced by patients’ psychosocial conditions (e.g., catastrophizing, and underreporting). Another way to measure pain is to measure the intensity based on clinician’s observation such as Observer Pain Intensity (OPI) system. However, OPI measurement is restricted by human’s limited capacity in quantifying pain and heavily relies on the physician’s subjective judgment. An objective measure for assessing pain minimizing both reporting bias from patients and observing bias from physicians is needed for research and clinical practice. Quantitative detection of pain in a continuous, automatic and real-time manner will enable timely responses to clinical conditions by physicians and improve hospital experiences of patients.

Despite the fact that humans are capable of reading facial information as a natural facial expression processing system, this capacity is limited to simple and large apparent discrepancies in features. Naturally, scientists have turned their interests to developing computational algorithms to train machines to decode complicated association between facial expressions and pain. Compared with human, machine learning algorithms are able to utilize many different facial features including landmarks, colors, lighting, and movements to detect human emotion. Recent advances in emotion recognition from face image and video benefit significantly from the wide adaptation of convolutional neural networks and increasing volumes of data. Machine-based pain assessment is expected to be more accurate and less biased compared with human observations and its scalability is priceless for clinical utilizations.

1.1. Objectives

The primary objective of our meta-analysis is to assess the accuracy (Outcome, O) of automatic machine learning algorithms (Intervention, I) compared with golden standard VAS report (Control, C) for assessing pain intensity among pain patients population (Population, P). In addition, we plan to conduct subgroup analysis to compare accuracy, generalizability, interpretability and computational efficiency by different types of machine learning methods used in order to suggest optimal method for applications in different medical settings. We intend to make suggestions on future strategies of ensemble learning and federated learning, both of which integrate different models, in automatic pain detection. We have conducted a thorough search on PubMed, Cochrane, and PROSPERO databases and our systematic review (SR) and meta-analysis is the first systematic review and meta-analysis on this topic.

2. Methods and analysis

2.1. Study registration

This protocol review has been registered on PROSPERO (Registration number: CRD42018103059).

2.2. Research question development (PICO)

The study research question was developed using the PICO research framework. Details are reported in Table 1.

2.3. Eligibility criteria

All studies in medical settings describing accuracy and performance of machine learning algorithms for automatic pain assessment using human facial expressions are eligible for inclusion. We also include review articles (no related SR and MA articles from our preliminary search) for their reference lists. Exclusion criteria include:

1. not a human study;
2. not clinical pain related;
3. algorithms not based on facial expression information;
4. not a quantitative study (except reviews);
5. no measurement of algorithm accuracy (no primary outcome);
6. clinical pain scores are not used in model building;
7. facial expression data not in image or video format.

2.4. Information source

A global search strategy will be systematically applied in three major public-available electronic medical and technical databases including Web of Science, PubMed, IEEE Xplore Digital Library from 2008 January to most current time (2018 December). Reference lists attached in eligible review articles will be retrieved and screened by author DL and DC. Related professional meeting abstracts and preprints (e.g., IEEE conferences, Pain conferences, arXiv.org) will be searched to account for publication bias. Study language is limited to English.

2.5. Searching strategy

Searching strategy is developed using keywords including pain, facial expression, detection, machine learning, deep learning, recognition, and emotion. Details of searching strategy for PubMed and other databases are provided in Table 2.

---

**Table 1**

**PICO research question development.**

| Name     | Description |
|----------|-------------|
| Population | Adult patients experience pain (e.g., chronic, acute) |
| Intervention | The intervention will be pain assessment estimated using computer-based facial recognition algorithms. |
| Control   | The study control/comparator will be self-reported or observed pain measurements, which is the most commonly used evaluation system for pain (e.g., NRS, VAS). |
| Outcome   | Primary outcome: Model accuracy by predicted assessment measures type: 1. Numeric score: Mean Standard Error (MSE) or equivalence; 2. Categorical pain degree (Y/N; No/Mild/Moderate/Severe); Conformance statistic (AUC ROC) or equivalence. Secondary outcomes: 1. Generalizability; 2. Interpretability; 3. Computational Efficiency. |

AUC ROC = area under curve for receiver operating characteristic curve, MSE = Mean Standard Error, NRS = Numeric Rating Scale, PICO = population, intervention, control, outcome, VAS = Visual Analog Scale.
2.6. Data management

Study record information including title and abstract from searched online databases will be downloaded and imported into Abstrackr platform developed by Brown University.[27] This platform will track and backup all activities when authors conducting the literature review process. Once eligible studies are identified, full-text article will be downloaded data extraction. A data collection sheet is used for study information extraction and storage and this file will be later uploaded to Systematic Review Data Repository (SRDR) website. All data and related logs will be uploaded to Open Science Framework (OSF) website for transparency and version control, if feasible.

2.7. Study selection

Two authors (DL and DC) will independently review and screen the titles and abstracts to identify eligible trials according to the inclusion and exclusion criteria using the Abstrackr platform. Disagreements between evaluators were resolved by consensus or consultation with a third investigator (HD or WZ). Excluded studies will be listed in PRISMA flowchart specifying reasons for their exclusion in Figure 1.

**Table 2**

| Searching strategy. |
|---------------------|
| **PUBMED** |
| #1 facial[Title/Abstract] and pain[Title/Abstract] and expression[Title/Abstract] |
| #2 “2008”[Date - Publication]: “2018”[Date - Publication] |
| #3 (recognition[Title/Abstract]) or (detection[Title/Abstract]) or (painful[Title/Abstract]) or (machine learning[Title/Abstract]) or (deep learning[Title/Abstract]) or (algorithm[Title/Abstract]) or (neural network[Title/Abstract]) or (SVM[Title/Abstract]) or (computer vision[Title/Abstract]) |
| #4 #1 and #2 and #3 |
| **IEEE** 2008 to 2018 facial and pain |
| **Web of Science** TS=(pain and (facial or face) and (automatic or detection or machine learning or deep learning) and (recognition or automatic or estimation or expression or emotion)) and TI=pain |

| Additional records identified through other sources |
|---------------------------------------------------|
| • Meeting abstract n = |
| • Arvix.org n = |
| • Others n = |

| Records excluded (n =) |
|------------------------|
| • not human study n = |
| • not about clinical pain n = |
| • not using facial expression n = |
| • not quantitative, or systematic reviews, meta-analysis n = |
| • duplicates n = |

| Records excluded (n =) |
|------------------------|
| • not about facial expression based computer algorithm n = |
| • no measurement of model performance n = |
| • not using pain score for model building n = |

**Figure 1.** PRISMA 2009 flow diagram.
2.8. Data extraction and collection

The full text will be downloaded and study information will be extracted by DL and DC. They will extract study-level data using a prepared data extraction form. An example of data extraction table is enclosed in Table 3.

2.9. Collected data items

Data items apart from outcomes collected for this meta-analysis will be divided into 4 blocks:

1. study information including study year, author information, type of study, journal name, and PICO elements;
2. database information including name of the database used for modeling, name of the hosting organization of the database, sample size of the database, and the funding or sponsorship information;
3. patient demographic information including gender, age, race, disease diagnosis, and acute or chronic pain;
4. machine learning method information including machine learning model type, optimization algorithm, and type of input feature.

2.10. Machine learning methods

Wide ranges of machine learning methods have been developed for automatic pain prediction from human facial expression. These machine learning methods used in eligible studies can include many different general categories of models like linear regression, Naive Bayes, logistic regression, support vector machine, Gaussian Processes, random forests, genetic algorithms, and artificial neural networks. When analyzing these methods in details, each machine learning model can be represented by several technical attributes including: what features the method utilizes (e.g., facial landmarks, raw face images), the underlying mathematical model (e.g., artificial neural networks, random forests), and the computational algorithm to find the optimum solution (e.g., stochastic gradient descent, Bayesian variational inference).

2.11. Study outcomes

Our outcomes are selected for assessing the overall pain assessment performance of studied machine learning methods. The primary outcome is model accuracy estimate (e.g., area under curve for receiver operating characteristic curve [AUC ROC]; F1 score, and proper score function such as brier score if available) to correctly predict pain intensity. Secondary outcomes include different aspects of utility measures such as generalizability, interpretability, and computational efficiency.

2.11.1. Primary outcome: standardized measurement of model predicting accuracy.

We expect the high degree of heterogeneity in experimental setting, populations, methods, outcome reporting, therefore, the primary goal is a descriptive summary of these issues. Predicting accuracy of the model typically shall include 2 parts of information: accuracy and calibration. However, computer science studies rarely report calibration results; therefore, our study will mainly focus on the accuracy performance of predictive accuracy of machine learning models. For regression algorithms, all measurements of error measurement, including Mean Absolute Error (MAE), will be converted to Mean Square Error (MSE) for comparison if possible. All correlation measurements will be converted to ranked correlation (Spearman correlation). For classification algorithms, all the accuracy measurement will be converted to AUC ROC and F1 score. The measurements that cannot be standardized will be reported as original values. If diagnostic test accuracy (DTA) measures including sensitivity and specificity were reported, this information will also be collected and analyzed depending on study data availability.

2.11.2. Secondary outcomes: generalizability, interpretability and computational efficiency.

For descriptive purpose only, a subjective comprehensive judgment will be given to each method at the model level about how generalizable and interpretable the model is. The levels of the judgment rank from High, Moderate, Low and Very Low. Computational efficiency will be analyzed if benchmark time for running the model is provided.

2.12. Incomplete information and missing data

If essential information is missing, we will attempt to collect the data by contacting the authors of the studies. If we fail to obtain sufficient data, these studies will be omitted from the data synthesis.

2.13. Risk of bias in individual studies

A novel risk of bias evaluation tool will be custom designed for this study similar to the Cochrane Risk of Bias tool. The risk of bias in eligible studies will be evaluated at 3 domains including:

1. input data selection,
2. model performance and
3. result reporting.

Factors influencing input data selection include database sponsorship (e.g., organization or single study data), and image/video quality (e.g., Dpi of video, camera setting). Factors

| Table 3 |
| --- |
| An example of variables collected in data extraction table. |

| Study information | Year of the study published |
| --- | --- |
| Author information | Last name of author |
| Type of study | SR, MA, methods paper |
| Journal name | Journal name |
| PICO elements | PICO elements in summary |
| Database information | Name of the database used for modeling |
| Host organization | Name of the hosting organization of the database |
| Sample size | Sample size of the database |
| Sponsorship | The funding or sponsorship information |
| Gender | Gender of participants (all, only male, only female) |
| Age | Age distribution |
| Race | Race/country of participants |
| Disease diagnosis | Disease diagnosis |
| Pain type | Acute or chronic pain |
| Machine learning method information | Machine learning model type |
| Optimization algorithm | The optimization method for model |
| Type of feature input | Video or photo, dpi, facial landmarks,... |
| Model output | Deliverable score for clinical use |

MA=meta-analysis, PICO=population, intervention, control, outcome, SR=systematic review.
influencing model performance include research team (e.g., whether there is a professional computer scientist or mathematician), innate prior of machine learning algorithm, algorithm training process, and evaluation method. Factors introducing reporting bias include incomplete reporting, selective reporting, non-standard reporting (e.g., only report point estimate without standard errors or confidence intervals). Based on these domains, risk of bias of eligible studies will be categorized into low risk, moderate risk, high risk, and unclear and presented. In as separate effort to demonstrate the quality of included domains, risk of bias of eligible studies will be categorized into standard errors or confidence intervals. Non-standard reporting (e.g., only report point estimate without reporting bias include incomplete reporting, selective reporting, training process, and evaluation method. Factors introducing whether there is a professional computer scientist or mathematician, heterogeneity is detected, we will use a heterogeneity among the studies. If no evidence of statistical heterogeneity is detected, C-statistic (AUC ROC) for classification model and MSE for regression model along with their 95% confidence intervals will be used for assessing accuracy. The Galbraith plot, Higgins and Thompson I-square will be used to assess heterogeneity among the studies. If no evidence of statistical heterogeneity is detected, we will use a fixed-effects model. If considerable heterogeneity is indicated (I-square > 50%), we will pool the summary measures across the studies using random-effects model optimized using Laird and DerSimonian method. Additionally, we will also search for the possible sources of heterogeneity from both clinical and methodological perspectives to provide an explanation or will consider conducting subgroup analysis. Meta-regression will be considered, if applicable. Extracted outcome data stored in SRDR will be imported into RevMan V.5.2.1 software and R V3.3.2 for analyses.

2.15. Subgroup analyses

We intend to conduct subgroup analyses by machine learning model types (e.g., regression vs classification; neural networks vs traditional machine learning), facial data input format and pain condition (e.g., chronic pain vs acute pain), if feasible.

2.16. Publication bias

We will search related professional meeting abstracts and technical preprints to account for publication bias. Publication bias will also be assessed using Contour-Enhanced Funnel Plots.

2.17. Confidence in cumulative evidence

Confidence in cumulative evidence will be conducted in accordance with the GRADE guideline. Inconsistency will be assessed using I-square test and Galbraith plot as described in the previous section. Indirectness will be assessed by examining the collected PICO elements of eligible studies and comparing generalizability (one of our second outcomes). Imprecision will be assessed by examining the study sample sizes and confidence intervals of interesting outcomes.

3. Discussion

In the era of artificial intelligence, computers start to outperform human in many fields. Machines now can perform well in identifying movements and certain behaviors from image and video information. These technical advancements provide a potential opportunity for automatizing pain detection and assessment using machine-observed facial information in real-world clinical settings. However, curation of large interventional study data sets of human pain scores with facial expression information is still challenging with both practical difficulties and ethical concerns. This lack of training data limits both accuracy and generalization of trained machine learning models. Additionally, good interpretability and computational efficiency are important elements for real-time information streaming between patients and clinicians for clinical utility. In this study, we propose a protocol for a systematic review and a meta-analysis on machine learning methods in automatic pain assessment from facial expression aiming to provide a useful reference for implementation of automatic pain management and collection of patient-produced data for clinicians and researchers.

Author contributions

Conceptualization: Dianbo Liu, Dan Cheng
Data curation: Dianbo Liu, Hao Deng, Wei Zhang
Funding acquisition: Wei Zhang, Dan Cheng
Search strategy: Dianbo Liu, Dan Cheng
Methodology: Dianbo Liu, Dan Cheng, Wei Deng
Writing – original draft: Dianbo Liu, Dan Cheng
Writing – review & editing: Wei Zhang, Hao Deng
Supervision and Project Administration: Hao Deng, Wei Zhang
Conceptualization: Dianbo Liu, Dan Cheng, Wei Zhang, Hao Deng
Data curation: Dianbo Liu, Dan Cheng, Hao Deng
Formal analysis: Dianbo Liu, Dan Cheng
Funding acquisition: Wei Zhang
Methodology: Dianbo Liu, Dan Cheng, Timothy Houle, Lucy Chen, Wei Zhang, Hao Deng
Project administration: Wei Zhang, Hao Deng
Resources: Wei Zhang, Hao Deng
Supervision: Wei Zhang, Hao Deng
Validation: Dianbo Liu, Dan Cheng
Visualization: Dianbo Liu, Dan Cheng
Writing – original draft: Dianbo Liu, Dan Cheng, Hao Deng
Writing – review & editing: Timothy Houle, Lucy Chen, Wei Zhang, Hao Deng

References

[1] Witte W. Pain and anesthesiology: aspects of the development of modern pain therapy in the twentieth century. Anaesthesist 2011;60:533–66.
[2] Bahreini M, Jalili M, Moradi-Lakeh M. A comparison of three self-report pain scales in adults with acute pain. J Emerg Med 2015;48:10–8.
[3] Ashraf AB, Lucy S, Cohn JF, et al. The painful face—pain expression recognition using active appearance models. Image Vis Comput 2009,27:1788–96.
[4] Le May S, Ballard A, Khadra C, et al. Comparison of the psychometric properties of 3 pain scales used in the pediatric emergency department:
visual analogue scale, faces pain scale-revised, and colour analogue scale.

[5] Ngu SSC, Tan MP, Subramanian P, et al. Pain assessment using self-reported, nurse-reported, and observational pain assessment tools among older individuals with cognitive impairment. Pain Manag Nurs 2015;16:595–601.

[6] Hjermstad MJ, Fayers PM, Haugen DF, et al. Studies comparing numerical rating scales, verbal rating scales, and visual analogue scales for assessment of pain intensity in adults: a systematic literature review. J Pain Symptom Manage 2011;41:1073–93.

[7] Chanques G, Viel E, Constantin J-M, et al. The measurement of pain in intensive care unit: comparison of 5 self-report intensity scales. Pain 2010;151:711–21.

[8] von Baeyer CL, Spagrud LJ, McCormick JC, et al. Three new datasets supporting use of the Numerical Rating Scale (NRS-11) for children’s self-reports of pain intensity. Pain 2009;143:223–7.

[9] Camann W. Visual analog scale scores for labor pain. Anesth Analg 1999;88:1421–9.

[10] Bijur PE, Silver W, Gallagher EJ. Reliability of the visual analog scale for measurement of acute pain. Acad Emerg Med 2001;8:1153–7.

[11] Breivik H. Fifty years on the Visual Analogue Scale (VAS) for pain-intensity is still good for acute pain. But multidimensional assessment is needed for chronic pain. Scand J Pain 2016;11:150–2.

[12] LeBaron S, Zeltzer L. Assessment of acute pain and anxiety in children and adolescents by self-reports, observer reports, and a behavior checklist. J Consult Clin Psychol 1984;52:729–38.

[13] Forsythe LP, Thorn B, Day M, et al. Race and sex differences in primary appraisals, catastrophizing, and experimental pain outcomes. J Pain 2011;12:36:1–72.

[14] Lee JJ, Lee MK, Kim JE, et al. Pain relief scale is more highly correlated with numerical rating scale than with visual analogue scale in chronic pain patients. Pain Physician 2015;18:E195–200.

[15] Kristiansen FL, Olesen AE, Brock C, et al. The role of pain catastrophizing in experimental pain perception. Pain Pract 2014;14:E136–45.

[16] Kipping K, Maier C, Bussemas HH, et al. Medication compliance in patients with chronic pain. Pain Physician 2014;17:81–94.

[17] Zhou J, Hong X, Su F, Zhao G. Recurrent convolutional neural network regression for continuous pain intensity estimation in video. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops 2016;84–92.

[18] Hadjistavropoulos T, Craig KD. A theoretical framework for understanding self-report and observational measures of pain: a communications model. Behav Res Ther 2002;40:551–70.

[19] Hill ML, Craig KD. Detecting deception in facial expressions of pain: accuracy and training. Clin J Pain 2004;20:415–22.

[20] Jack RE, Schyns PG. The human face as a dynamic tool for social communication. Curr Biol 2015;25:R621–34.

[21] Wegryn M, Vogt M, Kireclioglu B, et al. Mapping the emotional face. How individual face parts contribute to successful emotive recognition. PLoS One 2017;12:e0177239.

[22] Albergante L, Liu D, Palmer S, et al. Insights into biological complexity from simple foundations. Adv Exp Med Biol 2016;915:295–305.

[23] Littlewort GC, Bartlett MS, Lee K. Automatic coding of facial expressions displayed during posed and genuine pain. Image Vis Comput 2009;27:1797–803.

[24] Lucey P, Cohn JF, Matthews I, et al. Automatically detecting pain in video through facial action units. IEEE Trans Syst Man Cybern B Cybern 2011;41:664–74.

[25] Rudovic O, Lee J, Dai M, et al. Personalized machine learning for robot perception of affect and engagement in autism therapy. Sci Robot 2018;3: 1802.01186–01186.

[26] Moher D, Shamseer L, Clarke M, et al. Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. Syst Rev 2015;4:1–9.

[27] Wallace BC, Trikalinos TA, Lau J, et al. Semi-automated screening of biomedical citations for systematic reviews. BMC Bioinformatics 2010;11:65.

[28] Liu D, Peng F, Shea A, et al. DeepFaceLIFT: interpretable personalized models for automatic estimation of self-reported pain. J Mach Learn Res 2017;66:1–6.

[29] Khan RA, Meyer A, Konik H, et al. Pain detection through shape and appearance features. In: 2013 IEEE International Conference on Multimedia and Expo (ICME) 2013;1–6.

[30] Shuster JJ. Review: Cochrane handbook for systematic reviews of interventions, Version 5.1.0, published 3/2011. Julian P.T. Higgins and Sally Green, Editors. Research Synthesis Methods. 2011; 2:126–30.

[31] Moons KGM, Altman DG, Rovers MJ, et al. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): explanation and elaboration. Ann Intern Med 2015;162: W1–73.