

Risk prediction tools in cardiovascular disease prevention: A report from the ESC Prevention of CVD Programme led by the European Association of Preventive Cardiology (EAPC) in collaboration with the Acute Cardiovascular Care Association (ACCA) and the Association of Cardiovascular Nursing and Allied Professions (ACNAP)

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Xavier Rossello^{1,2}, Jannick AN Dorresteijn^{3, 4}, Arne Janssen⁴, Ekaterini Lambrinou^{4,5}, Martijn Scherrenberg^{6,7}, Eric Bonnefoy-Cudraz⁸, Mark Cobain⁹, Massimo F Piepoli¹⁰, Frank LJ Visseren² and Paul Dendale^{6,7}

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Abstract

Risk assessment and risk prediction have become essential in the prevention of cardiovascular disease. Even though risk prediction tools are recommended in the European guidelines, they are not adequately implemented in clinical practice. Risk prediction tools are meant to estimate prognosis in an unbiased and reliable way and to provide objective information on outcome probabilities. They support informed treatment decisions about the initiation or adjustment of preventive medication. Risk prediction tools facilitate risk communication to the patient and their family, and this may increase commitment and motivation to improve their health. Over the years many risk algorithms have been developed to predict 10-year cardiovascular mortality or lifetime risk in different populations, such as in healthy individuals, patients with established cardiovascular disease and patients with diabetes mellitus. Each risk algorithm has its own limitations, so different algorithms should be used in different patient populations. Risk algorithms are made available for use in clinical practice by means of – usually interactive and online available – tools. To help the

¹Centro Nacional de Investigaciones Cardiovasculares (CNIC), Spain

²Centro de Investigación Biomédica en Red en Enfermedades Cardiovasculares (CIBERCV), Spain

³Department of Vascular Medicine, University Medical Center Utrecht, The Netherlands

⁴Clinical Research Department Cardiology, Heartcentre Hasselt, Jessa Hospital, Hasselt, Belgium

⁵Department of Nursing, Cyprus University of Technology, Cyprus

⁶Jessa Hospital, Heartcentre Hasselt, Belgium

⁷Faculty of Medicine and Life Sciences, Hasselt University, Belgium

⁸Department of Cardiology, Hôpital cardiologique de Lyon, France

⁹Department of Cardiovascular Medicine, Imperial College, UK

¹⁰Heart Failure Unit, Cardiology, G da Saliceto Hospital, Italy, Keck School of Medicine, University of Southern California, Los Angeles, CA, USA

Corresponding author:

Xavier Rossello, Centro Nacional de Investigaciones Cardiovasculares (CNIC) Carlos III, Melchor Fernández Almagro 3, 28029 Madrid, Spain.
Email: frrossello@cnic.es

clinician to choose the right tool for the right patient, a summary of available tools is provided. When choosing a tool, physicians should consider medical history, geographical region, clinical guidelines and additional risk measures among other things. Currently, the U-prevent.com website is the only risk prediction tool providing prediction algorithms for all patient categories, and its implementation in clinical practice is suggested/advised by the European Association of Preventive Cardiology.

Keywords

Risk prediction, risk assessment, cardiovascular disease, prevention, patient

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Background

Cardiovascular disease (CVD) remains a worldwide leading cause of mortality and morbidity, despite the huge effort in improving clinical outcomes in recent decades.^{1–4} Guidelines on the prevention of CVD recommend the use of risk prediction tools to identify those at highest risk of CVD and provide to them preventive measures.⁵ Risk assessment and predicting survival have thus become pivotal to the prevention of CVD by enhancing healthier lifestyles, pharmacological and other healthcare interventions and reducing risk factor prevalence (e.g. smoking). Accessible and user-friendly risk assessment tools may be broadly used in all populations, no matter the baseline risk. Unfortunately, CVD risk assessment in clinical practice across Europe is not adequate,⁶ as illustrated by a report from The Netherlands highlighting the gap between positive policy intent and implementation of CVD risk assessment in practice.⁷ As the population is ageing and the prevalence of obesity and diabetes increases^{8,9} the need for a more personalised approach and repeated cardiovascular risk assessment is more urgent. Taking into consideration the variation between and within countries in risk assessment implementation,¹⁰ the current paper reviews the rationale for using risk prediction tools as well as a compilation of the currently available tools that make risk algorithms available for use in clinical practice. Also, it provides additional support to clinicians on when, to whom and how to use these tools. Special attention is taken of some subgroups of patients, such as young adults, elder individuals and patients with diabetes or other risk factors. This report is the result of the third phase of the European Society of Cardiology (ESC) Prevention of Cardiovascular Disease Programme run by the European Association of Preventive Cardiology (EAPC) in collaboration with the Association of Cardiovascular Nursing and Allied Professionals (ACNAP) and the Acute Cardiovascular Care Association (ACCA).

Rationale for the use of risk prediction tools

Traditionally, physicians have estimated prognosis by qualitatively integrating the patient's characteristics, clinical

signs and laboratory tests. The relative weight that clinicians assign to each clinical feature relies on their clinical judgement, previous experience and personal beliefs but the interpretation of this set of data may be inaccurate. An incorrect estimation of the prognosis might generate a mismatch between the risk profile of the patient and the type of care required. The alternative to clinical judgement alone is to apply risk prediction tools from multivariable algorithms, in which relative weights are assigned to each predictor in order to calculate the likelihood of a specific outcome over a specified time.¹¹ These tools provide information about prognosis in a more reliable and unbiased way.

The main purpose of risk prediction is to support informed treatment and triage decisions about initiation, discontinuation or intensification of preventive medication. In general, it is considered that 'high-risk' patients benefit the most from risk factor treatment in terms of absolute risk reduction. Subgroup analyses in meta-analyses of trials on lipid-lowering, blood pressure-lowering and antiplatelet therapy show that the relative risk reduction is more or less the same in all patients.^{12–14} This means that the individual absolute risk reduction and individual number needed to treat are solely determined by individual baseline cardiovascular risk.

How to use the tools with our patients

Risk prediction tools are usually developed with two main objectives: to assist healthcare professionals in their clinical decision-making process, and to inform individuals about their risks of developing an outcome. This section focuses on how the information provided by risk prediction tools is managed from a clinician and from a patient perspective.

Risk prediction tool use for clinicians

Risk prediction tools are not developed to replace doctors, but to provide objective risk estimates to assist health professionals in their subjective interpretations. It is implied that the correct risk stratification of individuals improves

clinical outcomes and resources allocation, avoiding both the overtreatment of low-risk individuals and the undertreatment of high-risk patients with the additional goal of promoting lifestyle changes in those at long-term risk.¹⁵ The overtreatment of patients may imply unnecessary medication-related side effects as well as a financial burden, whereas undertreatment may imply a higher risk of event recurrence. The rationale behind treating high-risk patients is supported by the results of randomised controlled trials that have shown that treatment of higher-risk individuals results in substantially greater reductions in absolute risk, even though relative risk reductions may be very similar in individuals with a higher and lower total risk.¹⁶ This should not be interpreted as suggesting that risk factor modification is not efficacious in low-risk individuals. Moreover, most risk prediction tools assume that the reduction in relative risk for benefit stays the same for all risks, whereas harm remains comparatively fixed. Although generally true, this assumption may not always hold. For example, patient characteristics associated with increased bleeding risk result in a lower individual net benefit of antithrombotic medication. Hence, an evidence-based approach to individualising treatment should be taken in order to balance the benefits and harms of using or not using treatments.¹⁷

Some obstacles impede the routine application of risk prediction tools, such as the lack of time,¹⁸ a general disdain by clinicians towards prediction rules whose algorithmic simplicity seems to disrespect clinical complexity,¹⁹ and the presence of competing risk algorithms and multiplicity of models for the same outcome, which sometimes generate an impracticable situation in which the clinician has to decide which tool to use. Despite these obstacles limiting the application of risk prediction tools, their use by clinicians may help to provide objective estimates of outcome probabilities to complement their clinical intuition and guidelines, under the assumption that accurately estimated probability improves clinicians' decision-making and consequently patient outcomes. They should also help to reduce cardiovascular outcomes and morbidity, through the optimal use of medical resources and a reduction in overtreatment, costs and unnecessary side effects of medication.

Risk prediction tool use for patients

Risk prediction tools can eventually have an impact on individuals' health when their information (i.e. predicted risk stratification) changes individuals' behaviour, self-management decisions and even treatment decisions. The information obtained by a clinician regarding a predicted risk may be translated into meaningful actions, enabling patients to gain insight into their cardiovascular prognosis and anticipating the potential impact of some therapies, as well as empowering them to take part in the decision-making process.^{20,21} This may increase self-motivation for

therapy adherence and lifestyle change, including changes in nutrition, physical activity, relaxation training, weight management and participation in smoking cessation programmes for resistant smokers. It is equally important for shared decision-making also to present data on the side effects of treatment – presenting trial data on the risk of side effects of some treatments (i.e. statins) and showing the net benefits would be of great help to avoid misinformed patients,²² although little is known about predicting treatment harms except for bleeding risk algorithms.

To facilitate treatment and prevention of CVD, it is important for clinicians to individualise counselling on the basis of each patient's experiences, needs and circumstances of everyday life. Individualised counselling is key for getting patients motivated and committed to improve their health. Decision-making should be shared between the clinician and the patient (including the family), and previous unsuccessful attempts to change to a healthy lifestyle or take guideline-recommended treatment should be addressed setting realistic goals. Involving individuals in identifying and selecting the risk factors to change might be relevant to reinforce their commitment. Self-assessed cardiovascular risk through some online available tools, such as the heart age tools provided by either the Joint British Societies (JBS3) or the Framingham Study, might help individuals to increase awareness about their underlying diseases and potential benefit from a primary prevention perspective. Moreover, patient's healthcare can be maximised by the combination of the knowledge and skills of all available caregivers (doctors, nurses, psychologists, experts in nutrition and cardiac rehabilitation).²³

Risk prediction tool assessment

Risk algorithms development and performance assessment

Risk algorithms should be based on not too many, unambiguous, easy to measure, low cost and widely available and easy to understand (for healthcare provider and patient) factors. In most risk algorithms this is indeed the case. Each predictor has a weighting factor and by summing this all up in an arithmetic equation, a long-term risk prediction can be produced. Several features are used to define model performance (summarised in Table 1). The accuracy of scores is generally expressed as a c-statistic, reflecting the discriminatory capacity. The level of the c-statistic, however, does not fully reflect the clinical value of a risk algorithm,²⁴ as it also depends on the heterogeneity of the population that the model is tested in. For example, when a risk algorithm is tested in a selected trial population of very similar patients, the c-statistic will be low regardless of the discriminatory ability of the model. At some point, adding more risk factors to the model does not lead to significantly improved accuracy.²⁵ Equally

Table 1. Basic concepts defining predictive model performance.

Feature	Definition
Calibration	Degree of agreement between observed outcomes and predictions. It can be assessed graphically (i.e. plotting the observed proportions of the outcome for groups of patients with similar predicted risk, like deciles of predictions) or formally using the Hosmer–Lemeshow goodness of fit test.
Discrimination	Ability of the model to distinguish a patient with the outcome (i.e. death) from a patient without the outcome (i.e. alive). For a binary outcome, the concordance c-statistic can be interpreted similarly as the area under the receiver operating characteristic curve.
Internal validation	Assessment of the validity of claims for the underlying population where the data originated from ('reproducibility'). Common methods are cross-validation or bootstrap resampling.
External validation	Assessment of the validity of claims for 'plausibly related' populations ('generalisability'). A different cohort is needed to perform an external validation (i.e. using other temporal or geographical cohorts).
Decision-curve analysis	It offers insight into clinical consequences by determining the relationship between a chosen predicted probability threshold and the relative value of false-positive and false-negative results to obtain a value of net benefit of using the model at that threshold.
Net reclassification index	Measure of the net percentage of those who do and do not develop the outcome within the time period who are correctly reclassified to a different risk category when a new risk factor is added to the risk estimation system.

important for clinical practice is to know whether the predicted risk reflects the actual risk, also known as model calibration. When a risk algorithm is validated in a population external to the population it was derived in, and shows good calibration ('what you predict is what you observe') then it can reliably be used in clinical practice in that population. If, however, predicted and observed risks are not balanced, recalibration for the differences in baseline risk can be performed to make the risk algorithm more widely applicable in different geographical regions.²⁶

Clinical impact of prediction tools

The correct risk stratification of patients should improve clinical outcomes and resources allocation. They are useful for planning disease management of patients for a given risk profile, and for the selection of patients suitable for more advanced therapies. However, very few risk prediction tools have undergone formal impact analysis to determine whether they improve outcomes when used in clinical practice¹⁹ – the performance of randomised clinical trials to demonstrate clinical benefit of using a given prediction tool is controversial given the high number of patients and resources needed for this purpose. Instead, the potential value of risk algorithms is often demonstrated using decision curve analyses^{27,28} or cost-effectiveness analyses.²⁹

Designing and performing impact studies to assess risk prediction tools is not an easy task, as many resources are needed and funding is scarce for this purpose.¹⁹ Despite the lack of solid evidence, it is expected that the use of the estimates provided by risk prediction tools improves both patient self-management³⁰ and doctor therapeutic decision-making,³¹ and consequently improves patients' outcomes and the cost-effectiveness of care.

Predicting risk of cardiovascular events by patient groups

The risk of future cardiovascular events can be determined in various patient groups based on their different baseline cardiovascular risk and risk factors profile. Therefore, different cardiovascular risk algorithms are needed for different groups of patients. As advocated in most guidelines, predicting 10-year fatal and non-fatal cardiovascular events is current practice in patients without CVD and without diabetes mellitus.¹ Various risk algorithms are available, such as systematic coronary risk evaluation (SCORE) to predict 10-year risk of cardiovascular death in Europe, QRISK to predict composite outcome of coronary heart disease, ischaemic stroke, or transient ischaemic attack in the UK and the pooled cohort equations to predict 10-year risk of a first atherosclerotic CVD event (defined as a non-fatal myocardial infarction, coronary heart disease death, or stroke) in North America.^{1,32,33} The level of 10-year cardiovascular risk together with the level of risk factors (e.g. cholesterol, blood pressure) drives the decision about whether or not to initiate or intensify medical treatment of risk factors. Cut-off values differ between guidelines. The 2016 European guideline recommends classification based on cardiovascular mortality risk as low (<1%), moderate ($\geq 1\%$ to <5%), high ($\geq 5\%$ to <10%) or very high ($\geq 10\%$). Subsequently, recommendations for (intensity of) preventive treatment are different for each risk category. When the predicted 10-year risk lies close to a decisional threshold additional risk factors with reclassification potential could be considered if such information is available for a patient. Potential reclassification factors recommended by the 2016 European guideline are socioeconomic status, family history of premature CVD, body mass index, computed tomography coronary calcium score, presence of

atherosclerotic plaque in the carotid arteries and ankle-brachial index.

Risk prediction in older patients

Cardiovascular risk estimation works well in middle-aged patients, but may overestimate cardiovascular risk in elderly individuals as competing non-cardiovascular mortality risk is not accounted for. For example, the original SCORE risk algorithm cannot be used in people over 65 years as it would overestimate cardiovascular risk in the elderly.¹ Instead, a specific elderly risk score could be used.^{5,33–35} Importantly, the ESC guideline on cardiovascular risk management points out that risk factor treatment is still an effective approach at advanced age and could be considered, taking into account its potential impact on quality of life and life expectancy.¹ Quantifying cardiovascular risk in individual elderly individuals and estimating treatment benefit may support informed decision-making.

Risk prediction in young patients less than 50 years

Because age is the most important predictor of 10-year risk, standard risk algorithms cannot be used to identify younger individuals less than 50 years at very high relative risk who may have high lifetime risk. Young individuals with unfavourable risk factor levels are more likely to develop CVD early and may prematurely experience fatal or non-fatal cardiovascular events. So trying to identify who may be at such risk is an important challenge.¹ Therefore, the ESC guideline for cardiovascular risk management advises to screen for cardiovascular risk factors from the age of 50 years, but also suggests that there are arguments to start a risk factor screening from the age of 40 years. The differentiation of cardiovascular risk in younger people could be done by using a relative risk chart as presented in the guideline. The relative risk shows the risk of a person with several cardiovascular risk factors with respect to others of the same age with ideal levels of risk factors. Alternatively, clinicians should consider using a risk age calculator or a lifetime risk calculator.

The relevance of risk estimation in younger people is that they should be counselled on lifestyle factors with emphasis on avoiding smoking, overweight and sedentary behaviour. In addition, blood pressure and statin treatment could be considered in younger people with very high blood pressure and lipid levels. Recent methodological advances in prediction research have allowed for making lifetime risk and treatment benefit predictions that are presented in lifetime cardiovascular risk and in cardiovascular free life years gained from (combinations of) preventive medication.^{36,37} Shared decision-making is very important when using lifetime risk estimates for initiating preventive

treatments. This includes a comprehensive discussion of the risks and benefits of medication and understanding on the part of the patient.

Risk prediction in high-risk patients

Patients with diabetes mellitus and individuals with clinically established CVD are, on average, considered to be at high or very high cardiovascular risk, although their individual on-treatment residual risk for (recurrent) cardiovascular risk ranges from low to very high.^{38–40} This underlines the need for cardiovascular risk stratification and calls for specific risk prediction tools for patients with diabetes mellitus and for patients with clinically manifest vascular disease. Although formal threshold levels for risk classification and treatment decisions have not yet been established for these populations, the level of 10-year risk in these patients could help to determine who will benefit from intensive treatment of risk factors,^{41–44} and this could improve the cost-effectiveness of intensive treatment at a group level.^{42,45} Also, risk prediction can be used for communicating the personal cardiovascular risk to individual patients, illustrating the need for lifelong treatment and may motivate patients to adhere to treatment.

Importantly, the relationship between prognostic factors and the risk of atherosclerotic vascular disease is very different between patients with or without a previous cardiovascular event, although they share a common causal pathway. In prediction, the focus is not on defining causal effects but on reporting the prognostic value of one risk factor when combined with other risk factors. Hence, caution should be taken with some extrapolations: a limited predictive value of a given risk factor does not necessarily translate into a limited effect on preventing events when treating such a risk factor. Moreover, the presence of an ‘index event bias’ should be taken into account in secondary prevention.⁴⁶ This statistical phenomenon arises in studies that select patients based on the occurrence of an index event. Because of the congruence between risk factors for the index and recurrent events, there is a trend to converge effects of risk factors on recurrent events towards the null.⁴⁶ Although this is only considered as ‘bias’ in aetiological studies, the relevance of this statistical phenomenon on prognostic risk scores is that classic risk factors do not discriminate between high and low-risk individuals anymore. Therefore, risk scores for high-risk populations often include additional risk factors.

Compilation of online available prediction tools

Healthcare providers can get easily confused by the wide range of available risk algorithms. To help the reader to

Overview of freely accessible online tools for estimation of cardiovascular prognosis				
TOOL	Patient categories	Geographical region	Prediction outcomes	Additional features
SCORE www.heartscore.org	Healthy people	Europe high and low risk regions	10-year CVD risk	Personal health advice based on ESC-Guidelines Available in 17 languages Print option for patient handout Patient history and progress Calibrated versions
QRISK3 www.qrisk.org/three	Healthy people	United Kingdom	10-year CVD risk Relative risk Heart age	Infographics for patient communication
JBS-3 Risk calculator www.jbs3risk.com	Healthy people	United Kingdom	10-year CVD risk Lifetime CVD risk Heart age CVD-free life-expectancy	Effect of risk factor optimisation Infographics for patient communication
ASSIGN score www.assign-score.com	Healthy people	Scotland	10-year CVD risk	Missing data filled in by population average/median Print option for patient handout
PROCAM score Various websites	Healthy people	Germany	10-year coronary event risk	
CUORE www.cuore.iss.it/sopra/calc-rischio_en.asp	Healthy people	Italy	10-year CVD risk	Also available in Italian language
ASCVD risk-estimator plus http://tools.acc.org/ASCVD-Risk-Estimator-Plus	Healthy people	United States	10-year CVD risk Lifetime CVD risk	Effect of risk factor optimisation Personal health advice based on ACC/AHA guidelines Print option for patient handout
Framingham risk score www.framinghamheartstudy.org	Healthy people	United States	10-year CVD risk 30-year CVD risk Heart age	Additional calculators for other vascular disease outcomes
Reynolds Risk score www.reynoldsriskscore.org	Healthy people	United States	10-year CVD risk Relative risk	Effect of risk factor optimisation Projection of risk increase with advancing age Print option for patient handout
Globorisk www.globorisk.org	Healthy people	Worldwide	10-year CVD risk	Country adjusted risk charts available
UKPDS risk engine V2 www.dtu.ox.ac.uk/riskengine	Type 2 diabetes	United Kingdom	Fatal and non-fatal CVD risk for any risk interval	Print option for patient handout
ADVANCE risk engine www.advancerriskengine.com	Type 2 diabetes	Europe, Asia, Australasia and North America	4-year CVD risk	Missing data filled in by population average/median Additional calculator for kidney disease outcomes
SMART risk score www.escardio.org/Education/ESC-Prevention-of-CVD-Programme/Risk-assessment/SMART-Risk-Score	Vascular patients	Europe and United States	10-year CVD risk	Missing data filled in by population average/median
MAGGIC risk calculator www.heartfailureisrisk.org	Heart failure patients	Worldwide	1 and 3-year mortality risk	
Seattle Heart Failure model www.SeattleHeartFailureModel.org	Heart failure patients	Northern-America	1, 2 and 5-year mortality risk	Effect of specific treatment options
U-Prevent www.U-prevent.com	Healthy people Type 2 diabetes patients Vascular patients Elderly	Europe and Northern-America	10-year CVD risk Lifetime CVD risk CVD free life expectancy	Also available in Dutch Effect of specific treatment options Effect of deferred treatment Infographics for patient communication Print option for patient handout Missing data filled in by population average/median Calculator selection aid

Figure 1. Overview of freely accessible online prediction tools for estimation of cardiovascular prognosis.

find the most suitable risk algorithm for each patient, Figure 1 summarises all currently available and freely accessible online tools for the estimation of cardiovascular prognosis (search date: 27 July 2018). Tools not available in English were not assessed and therefore could not be listed in this figure. Also, because not all available risk algorithms have been converted to prediction tools, Figure 1 does not include all available risk algorithms.

Seven considerations for selecting the best prediction tool for every patient

1. The medical history is the first factor that needs to be considered when determining which is the most suitable and applicable tool for each patient. Most prediction tools available apply to healthy people without a vascular disease history only – in other words, the primary prevention population. Some of these tools include diabetes mellitus as a predictor variable. Yet, for a patient with diabetes, a diabetes-specific tool may result in more accurate

estimations. The ADVANCE-risk engine, for example, takes into account haemoglobin A1c, albuminuria, the presence of retinopathy, atrial fibrillation and duration of diabetes in addition to classic risk factors. Similarly, specific tools are available for patients with a vascular disease history. The SMART risk score^{39,47} takes into account the number of vascular disease locations, kidney function, high-sensitivity C-reactive protein (hs-CRP) and the number of years since the first diagnosis of vascular disease as important predictors in this patient category. Likewise, the MAGGIC risk calculator⁴⁸ and Seattle heart failure model,⁴⁹ estimate risk for patients with heart failure, be it all-cause mortality risk rather than CVD risk. Heart failure-specific predictors in most of the heart failure tools include New York Heart Association (NYHA) classification and ejection fraction.^{50–52} Most tools have an upper age limit, generally not much higher than 75–80 years. For estimating CVD risk in the elderly, a few algorithms are

available that account for competing non-vascular mortality. Examples are the JBS3 risk calculator³³ and the elderly risk score³⁴ and lifetime risk algorithms that are available in the U-Prevent tool. Such competing risk adjusted tools avoid the over-estimation of CVD risk in elderly patients. Finally, risk prediction tools in general are not suitable for every patient. Especially in the presence of life-limiting comorbidity, CVD risk predictions may not be accurate. Examples of such comorbidity include metastasised malignancy, severe pulmonary disease or end-stage renal disease. Also, predictions may be less accurate for patients with extreme risk factor levels, such as very high cholesterol in familial hypercholesterolemia.

2. Calibration: the geographical region and timeliness of the data that were used to develop and calibrate the risk algorithm need to be considered to understand which tools are validated in each clinical setting. This is important, because differences in lifestyle, environmental factors, genetic background of a population and quality of healthcare result in differences in event rates and life expectancy. These differences are usually incompletely expressed by the levels of measured risk factors. This is, for example, the reason why several countries have undertaken national recalibrations of the SCORE risk chart.¹
3. The choice of the appropriate tool may be restricted by clinical guidelines. For example, the ESC primary prevention guideline recommends the use of HeartScore for healthy people without vascular disease.¹ Similarly, the American College of Cardiology/American Heart Association (ACC/AHA) guideline recommends the pooled cohort equations risk estimator.³² Guidelines are less specific on which tool to use for patients with diabetes mellitus, vascular disease, heart failure or elderly patients.
4. Besides 10-year CVD risk, most tools provide additional risk measures, such as heart age, relative CVD risk, lifetime CVD risk and CVD-free life expectancy. These additional risk measures may be easier to explain to patients. Moreover, they may be more informative in younger people whose 10-year CVD risk is generally low and indiscriminate.
5. Some tools offer features that enable dealing with missing or unavailable values. In clinical practice, there is frequently limited availability of clinical information. On initial evaluation, total cholesterol and high-density lipoprotein cholesterol may not yet be measured, for example. Also, there is a need to evaluate cardiovascular risk in scenarios where resources are limited. A number of tools use the imputation of average risk factors. Alternatively,

lipids are replaced by body mass index in some models.⁵³

6. The estimation of the individual effect of preventive treatment is provided by only a few tools. This type of information could be communicated to patients and, therefore, support shared decision-making. In addition, such information may be motivational and possibly improve therapy adherence. Most tools estimate the effect of risk factor optimisation, for example, reaching optimal blood pressure and cholesterol values. The U-Prevent lifetime tools and Seattle heart failure model are a little bit more sophisticated, as they can be used to estimate the effect of specific treatment options, for example changing a statin dose or the addition of aspirin.
7. Risk score tools differ in their user-friendliness and timeliness of their interface. Most tools also offer additional features that may be considered helpful. These include language options, personalised guideline recommendations, infographics for patient education and a print-out option.

Recommendations

Based on these seven considerations, the EAPC advises the use of the U-Prevent tool (www.U-Prevent.com) in clinical practice. The U-Prevent tool is an interactive website that encompasses risk calculators for all categories of patients. These include the guideline-recommended risk algorithms for healthy people without CVD (i.e. SCORE and the pooled cohort equations),^{1,32} but also the SMART risk score³⁹ for vascular patients, the ADVANCE risk score for patient with diabetes mellitus⁵⁴ and a competing risk-adjusted elderly-specific score for people over 70 years.³⁴ In addition, U-Prevent offers innovative lifetime risk algorithms for each of these patient categories. These include the LIFE-CVD model for apparently healthy people aged 45–80 years,⁵⁵ the DIAL-model for diabetes patients aged 30–85 years⁵⁶ and the SMART-REACH model for vascular patients aged 45–80 years.⁵⁷ Figure 2(a) shows an overview of all of these risk algorithms that are available on the U-Prevent website. Figure 2(b) shows an example of a results interface of one of the U-Prevent lifetime calculators.

All U-Prevent risk algorithms have been extensively validated in contemporary European and North American populations and geographical updates are applied when appropriate. This tool has a timely and user-friendly interface and offers infographics that can support doctor–patient communication and shared decision-making in clinical practice. U-Prevent is targeted at all types of healthcare providers, working both in primary and secondary care and including both doctors and nursing specialists. In addition, the tool is also accessible to informed patients; however, it is not intended as a substitute for professional medical advice. Figure 3 shows a flowchart that can be used to determine

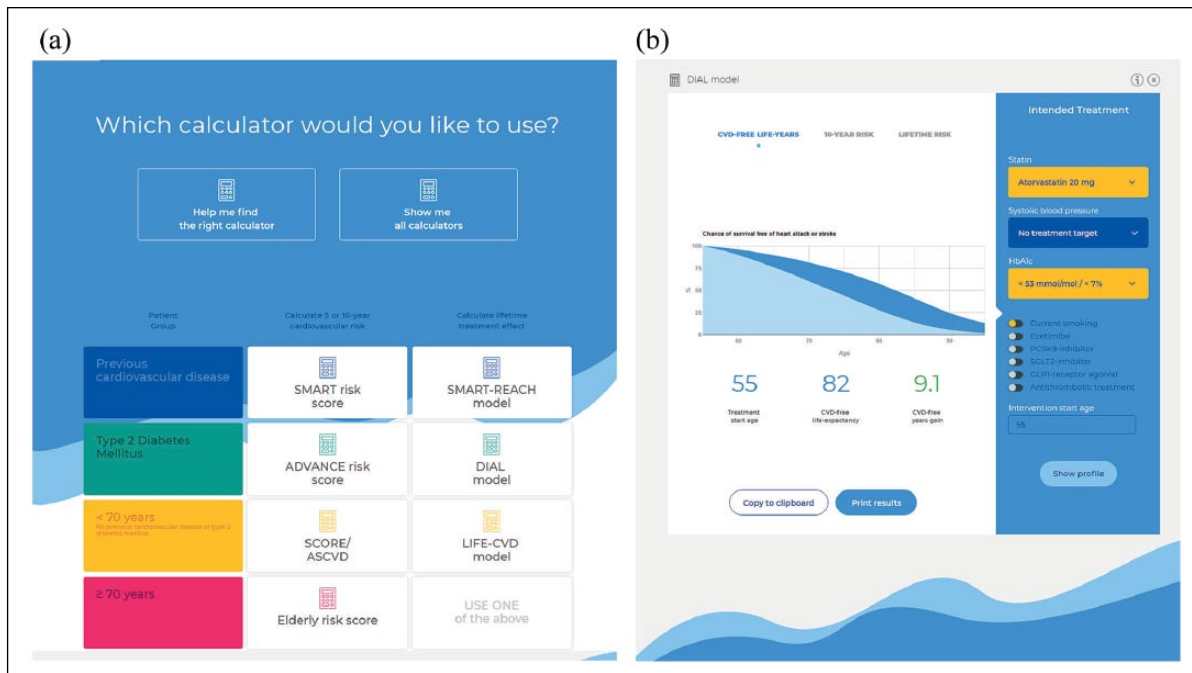


Figure 2. Screenshots of the U-Prevent tool at www.U-Prevent.com. (a) An overview of available risk algorithms for each patient category; (b) an example of a results screen based on the U-Prevent lifetime risk algorithm for diabetes patients, showing the estimated number of cardiovascular disease-free years gained with a combination of smoking cessation and a haemoglobin A1c target of less than 53 mmol/mol for a random 55-year-old patient with type 2 diabetes mellitus whose current medication is simvastatin 40 mg.

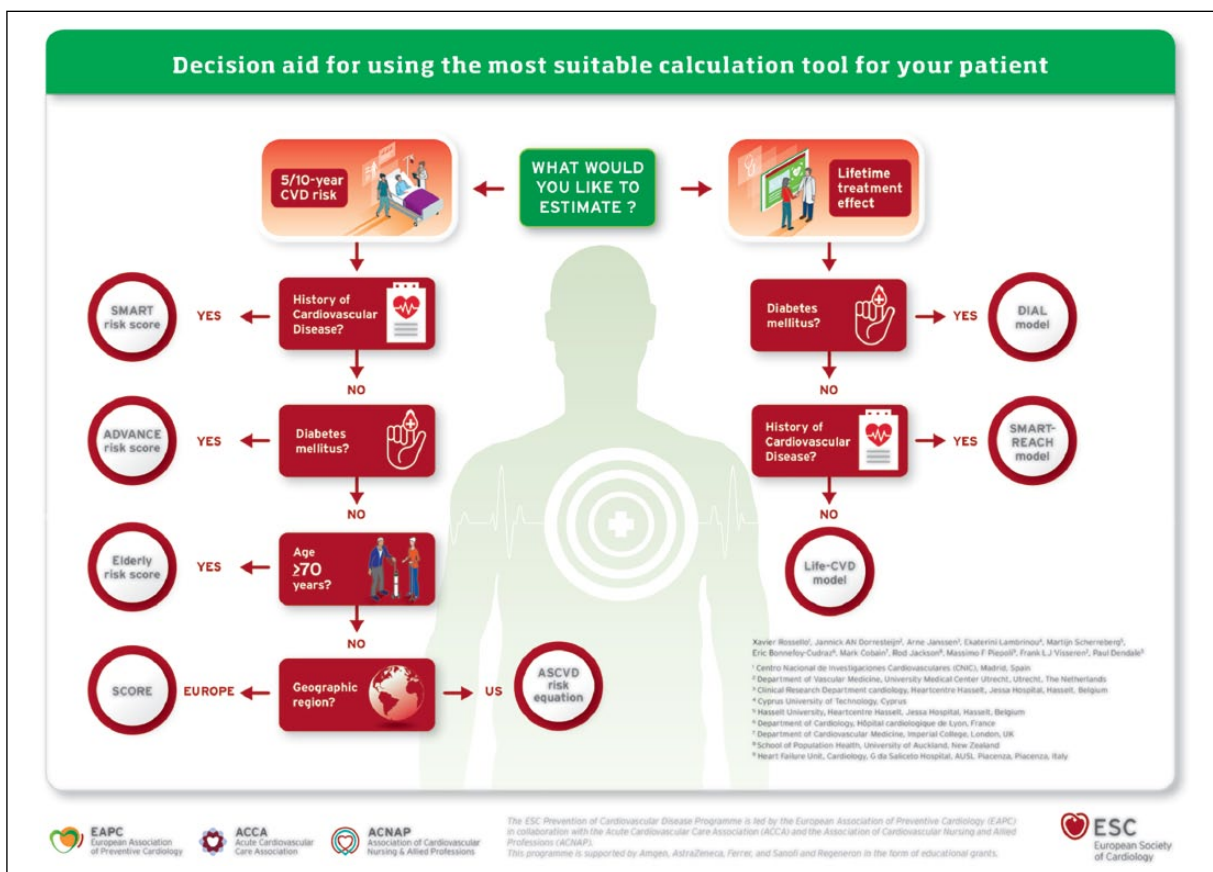


Figure 3. Decision aid for using the most suitable risk algorithm for every patient. All mentioned risk algorithms can be accessed on www.U-Prevent.com.

which U-Prevent algorithm can best be used based on the individual characteristics of a given patient. A calculator selection aid based on this flowchart can also be found on the U-Prevent website.

For the calculation of CVD risk in a healthy population, the EAPC advises the use of HeartScore (www.heartscore.org). HeartScore is aimed at supporting clinicians in optimising individual cardiovascular risk reduction. It is the interactive version of the SCORE risk charts and offers risk calculation and management advice in 17 languages. HeartScore allows patients' data storage, and facilitates the follow-up on risk reduction through progress graphs.

Conclusion

The EuroAspire survey teaches us that cardiovascular risk is often poorly managed. To address this, a quantification of risk at the level of the patient is useful. Unfortunately, risk stratification is not generally accepted in daily clinical practice.⁷ One possible reason is the presence of multiple tools for the same outcome, which creates confusion. The message of this paper is that for patient groups with different risk factor profiles and different baseline cardiovascular risk, different risk algorithms are to be used. An overview is provided of most available risk prediction tools, with their strengths and weaknesses.

The EAPC advises the use HeartScore for risk prediction in healthy people and the use of the U-Prevent tool developed by the University of Utrecht. U-Prevent provides risk algorithms for all patient subgroups and ages, and it offers a lifetime perspective for each subgroup. These lifetime risk algorithms make it possible to estimate the effect of specific medication changes in terms of the lifetime of the patient, and to calculate CVD-free life years gained. The U-Prevent makes available risk algorithms validated in contemporary European and North American populations including SCORE. HeartScore is currently being redesigned for mobile use, and the development of a mobile app for risk assessment and management is also planned within the ESC Prevention of Cardiovascular Disease Programme.

Author contribution

XR, JAND, AJ, EL, MS, FLJV and PD contributed to the conception or design of the work. XR, JAND, AJ, EL, MS, FLJV and PD drafted the manuscript. All authors critically revised the manuscript. All authors gave final approval and agree to be accountable for all aspects of the work ensuring integrity and accuracy.

Declaration of conflicting interests

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