From Smartphone Camera to Risk Score: Translating Functional Fitness Tests into CVD and Mortality Prediction

ACF Biomechanical Research BV

Executive Summary

This whitepaper makes the case for integrating simple, computer vision–standardized physical fitness tests into cardiovascular disease (CVD) and all-cause mortality risk assessment models. Traditional risk calculations largely ignore direct measures of physical fitness and functional capacity, even though extensive research links cardiorespiratory fitness, muscular strength, balance, and mobility to mortality and CVD outcomes.

ACF Biomechanical Research BV proposes a new battery of six tests (push-ups, squats, one-legged balance, vertical jump, overhead squat, and toe-touch) administered via smartphone-based computer vision. Each test is scored on a 0–100 scale, which is then fed into an interpretable Cox proportional hazards model alongside established predictors like age, sex, and BMI. This approach is designed to be practical, equipment-free, and broadly accessible, thus, overcoming common barriers that prevent fitness metrics from being included in standard clinical evaluations. However this risk assessment technique is not

Key highlights:

- **Evidence-Backed Rationale:** Decades of epidemiological data show that even basic fitness measures (e.g., push-up capacity, vertical jump, balance) have independent prognostic value for mortality and CVD.

- **Accessible and Scalable:** The proposed tests require minimal training, no special equipment, and leverage smartphone cameras for objective measurement—ideal for large-scale population assessment.

- **Interpretable but Evolving Model:** The whitepaper outlines a preliminary Cox model using literature-derived coefficients. The plan is to refine these estimates or migrate to machine learning as more large-cohort data become available.

- **Frailty Detection:** Tests like one-legged balance and overhead squat can flag mobility and flexibility issues often overlooked by traditional CVD-centric models yet correlated

with higher mortality risk as well as CVD risk.

- **Limitations and Next Steps:** Assumptions about scoring, missing data, and hazard ratios must be validated. Over time, replacing linear scoring and simplistic coefficients with ML-based “raw” data analysis will likely yield more precise risk stratifications.

By incorporating fitness metrics, this framework offers a more holistic view of physiological resilience than standard demographic and laboratory measures alone. While the current model relies on best-guess estimates from existing studies, it underscores the urgent need for broad, data-driven adoption of objective physical fitness assessments.

Simply put: if you want to reduce your risk of dropping dead early, sweat and lift heavy things regularly. We plan to measure exactly how much that helps.

Introduction:

Traditional risk models (e.g. Framingham or ACC/AHA Pooled Cohort equations) rely on demographics and clinical factors like blood pressure and cholesterol. While useful, these models largely omit direct measures of physical fitness and functional capacity, and these measures are increasingly recognized as powerful predictors of health outcomes. (1,2)

High cardiorespiratory fitness (CRF) levels can halve all-cause mortality risk compared to low fitness(2), and muscular strength has been shown to predict mortality even beyond traditional risk factors(2,3). However, CRF (typically measured by VO_2max or exercise testing) and strength assessments are seldom included in clinical risk assessments.

There is growing evidence that simple fitness tests carry significant prognostic information.(4–6,3). For example, men who can perform more than 40 push-ups have been shown to have significantly lower incidence of cardiovascular events over 10 years compared to those who can do fewer than 10(6).

Advances in computer-vision technology now enable simple, objective measurement of fitness tests, they not only count the number of repetitions performed but can help in determining whether the tests are performed according to objective standards, which is necessary for the usefulness of such tests as a predictive tool.

We hypothesize that adding easy-to-measure fitness metrics, such as; balance, muscular endurance, power, and flexibility to demographic factors will improve prediction of CVD events and all-cause mortality, using equipment that is ubiquitous, namely, smartphones. These fitness tests capture aspects of physiological resilience not reflected in conventional risk factors. For example, poor balance and mobility may indicate frailty, which is linked to higher mortality independent of disease diagnoses. (7,8).

We propose a continuous risk score, currently derived from an interpretable multivariable model(Cox proportional hazards model) which will later be replaced by ML-based approaches as we are able to gather more data on both the fitness tests and the future outcomes of the subjects. Our current approach uses assumptions and approximations that are less than ideally reliable due to lack of data.

Methodology:

The current battery of tests:

Our current battery of tests include two maximal effort tests of pushups and squats, a one legged balance test, a vertical jump test, an overhead squat assessment, and a standing toe touch test.

Our choice of these tests are resulting from several practical factors;

1- We want to keep the total test time as brief as possible, to ensure as large a participation as possible.

2- We want the tests to be done with no equipment, even basic ones like a standard height step, as each standardized piece of equipment no matter how low-cost it is, decreases the chance that any random person selected from a population will be able to self-administer these tests via smartphone.

3- We want the training requirements to perform each test as low as possible, again, to ensure the largest percentage of any given population will be able to use the full battery of tests.

Our rationale for including each test is as follows:

Push-ups in 60 seconds: We picked the 60 second pushup test due to the previously established epidemiological significance as found in a 2019 study(6). Our computer vision methods are able to distinguish satisfactory repetitions from unsatisfactory ones, thus providing an objective measurement.

Unlike the 2019 JAMA firefighter study that established a strong correlation in physically active men, there is no large longitudinal cohort that has tracked women’s push-up capacity against cardiovascular events or disease. However there are more limited studies which shows a link between pushup capacity and CVD risk, for example ability to perform more push-ups inversely correlated with carotid-IMT after multivariable adjustment(9).

Squats in 60 seconds: We were unable to find a study similar to the 2019 JAMA firefighter study involving squats but chose it under two assumptions;

1- The Ruffier Squat test is a Vo2Max approximation technique that uses squats, but requires taking of heart rate measurements, which have been omitted from our test for sake of simplicity, but will be optionally introduced later using automated measuring equipment, such as smart watches, fitness trackers or ppg techniques if the user lacks such equipment.

The model operates under the assumptions that individuals cease exercise repetitions only upon reaching their maximum heart rate, which is specific to their age and sex. Furthermore, it's assumed that their heart rate returns to a baseline level before the subsequent test commences. This serves as an analogue to taking actual measurements of their heart rate. This approach is yet untested and we don’t have correlation data to VO2max which we aim to rectify by adding more data.

2- Pushup test is harder to administer to women so we hypothesized that it may serve as an analogue to the pushup tests in women for assessing general bodily strength, since a good portion of the female population have trouble doing pushups, thus lowering the usefulness of the pushup test.

We record squat count (repetitions in 60 sec) as a continuous predictor. This serves as a field measure of CRF, which is a powerful independent predictor of mortality(2).

One legged balance: As shown in many studies, there is a very strong correlation between the performance in this test and all-cause mortality(7,10,11) in older individuals. While balancing ability and all-cause mortality in young people is not widely studied, we hypothesize that younger populations may show a similar link.

While this assumption about the balance ability of the young individuals is just that, an assumption, we think it is a reasonable one for our initial model. We will be refining this assumption based on data that we collect in the future.

Vertical Jump Height: Using pose estimation, we measure the maximal vertical jump height (in centimeters) the participant can achieve from a stationary position with arm swing. Vertical jump is a proxy for lower-body power (explosive strength) and has particular relevance in younger and middle-aged individuals, including athletes.

Muscle power declines earlier and faster than muscle strength with aging, and low power is associated with worse functional outcomes. In a Japanese cohort, men with the lowest vertical jump ability had over five times higher risk of CVD death compared to those with the highest jump results(3). We include vertical jump height as a continuous variable. A lower jump height indicates reduced muscular power, which may reflect underlying sarcopenia or poor neuromuscular function, linked to higher cardiometabolic risk.

Overhead Squat Mobility Test: This test is used as an assessment of musculoskeletal mobility and movement quality. The participant performs an overhead squat –holding arms overhead, squatting down. Our computer vision system evaluates whether the person can squat with thighs parallel to the ground without knees caving (pass/fail), and whether their torso and shin angle can be kept parallel. This test assesses flexibility in the ankles and shoulders along with hip mobility, and core stability.

We hypothesize that poor performance indicates increased risk of falls or orthopedic issues. Impaired musculoskeletal mechanics in performing non-endurance movements has been linked to mortality in other contexts. As an example, a low score on a sit-and-rise composite test was associated with a 5-fold higher all-cause mortality hazard(8). A poor score (inability to perform the movements) may flag frailty and risk of fractures; notably, hip fractures carry statistically significant one-year mortality in older adults(12).

Toe-Touch Flexibility Test: Toe touch serves as an assessment of musculoskeletal flexibility in the posterior chain. The participant performs a toe-touch from standing. Our computer vision system evaluates whether the person can touch their toes (by measuring wrist-to-floor distance) while also measuring their ability to do so with straight knees –which points to better posterior chain flexibility. We also analyze the curvature of their back throughout the movement, which gives us more data to come up with a better conclusion.

While we are not aware of a direct, proven mechanistic explanation of the relationship between poor flexibility to CVD risk, there is strong evidence of correlation to mobility and flexibility(13–15) exists. The relationship between the two may be explained by elastin-to-collagen ratio and on collagen cross-linking contributing to both joint ROM and aortic compliance(15).

Other metrics we use in our calculation in addition to the battery of tests:

Age (years): Continuous variable. Age is a fundamental risk factor (risk is expected to increase with age for both CVD and mortality).

Gender (male/female): Categorical indicator. Gender influences baseline risk (e.g. males often have higher middle-age CVD risk). The model will account for sex differences either by a gender variable or sex-specific calibration of other factors.

Weight and Height: Continuous measures (kg and cm) used to calculate BMI.

Our method of handling missing tests due to physical limitations:

If a participant cannot perform a test due to physical limitation (e.g. a musculoskeletal injury), the result is noted as missing and, for risk scoring, would be conservatively imputed as lowest performance (since inability often implies higher risk). The use of computer vision ensures objective quantification (time, count, distance) and reduces observer bias.

Our current assessment approach:

Each fitness test score (0 = worst, 100 = best) is included as an independent continuous predictor. Higher scores indicate better performance (greater strength, power, or flexibility), which generally correlates with lower risk. We develop two models, one for CVD risk and one for all-cause mortality. We assume linear effects for most, but note possible non-linearities, as in, diminishing returns at very high fitness. We expect these outliers to be more significant in higher scores opposed to lower scores. Our method of scoring each exercise does take into account these non-linearities, but these calculation techniques need to be improved by filling the gaps in data. Coefficients are chosen based on literature-derived hazard ratios for very broadly analogous measures and will be updated as more specific data becomes available to us.

We handle the codependence of certain metrics such as pushup capacity and gender differences in the initial scoring system that we have developed for each exercise, thus taking into account the difference across demographic strata.

By developing two models, we allow the possibility that certain fitness measures influence one risk and not the other. For example, a poor overhead squat result might elevate mortality risk (due to frailty or injury risk) without significantly changing one’s CVD risk estimation. Separating the models ensures each outcome’s predictor set is optimized and interpretable in context.

Model form: We propose a Cox proportional hazards model of the form:

$$h(t \mid X) = h\_0(t) \cdot exp(\beta\_Age \cdot Age + \beta\_Male \cdot Male + \beta\_BMI \cdot BMI + \beta\_PU \cdot PushUpScore + \beta\_SQ \cdot SquatScore + \beta\_Balance \cdot BalanceScore + \beta\_Jump \cdot JumpScore + \beta\_OHS \cdot OHS\_fail + \beta\_Flex \cdot FlexibilityScore)$$

CVD risk assessment:

We propose a Cox proportional hazards model that combines demographic risk factors with our battery of computer vision-quantified physical fitness tests (normalized 0–100 scores) to produce a relative 10-year CVD risk index. This index represents a continuous hazard ratio (HR) as in a proportional risk relative to a baseline, and not an absolute probability, which may also be derived using survival probabilities from events, but will introduce another layer of separation from the data found in clinical studies.

Predictor (unit change)	**Coefficient (β)**	**Hazard Ratio (HR)**
Age (per 1 year older)	0.067	1.07 (≈2× per decade)
Male Sex (1 = male)	0.693	2.0× risk for males vs females
BMI (per 1 kg/m²)	0.058	1.06 per +1 (≈1.30 per +5 kg/m²)
Push-Up Score (per +10 points)	–0.223	0.80
Squat Score (per +10 points)	–0.163	0.85
One-Leg Balance Score (per +10 points)	–0.105	0.90
Vertical Jump Score (per +10 points)	–0.174	0.84
Overhead Squat Fail (vs pass)	0.262	1.30× if fail
Flexibility Score (per +10 points)	–0.030	0.97

Cox proportional hazards model that outputs a relative 10-year CVD risk score using age, sex, BMI, and our physical fitness test battery scores that are normalized according to demographics. Each variable's coefficient is grounded in literature: better performance in push-ups, squats, balance, jump, overhead squat, and flexibility correlates with lower hazard, in agreement with epidemiological evidence. The model is formulated for interpretability, clinicians and patients can understand, for example, that improving a fitness score by 10 points might reduce one's CVD hazard by ~10–20% depending on the test.

All-cause mortality risk assessment:

Our all-cause mortality risk coefficients factor in the tests that correlate with frailty more strongly, however due to the lack of available data that covers all strata and risk factors equally we need to make assumptions which will need to be tested with cohort studies. This index represents a continuous hazard ratio (HR) as in a proportional risk relative to a baseline, and not an absolute probability.

The model form is the same as the CVD risks but using different weights for the coefficients.

Predictor (unit change)	**Coefficient (β)**	**Hazard Ratio (HR)**
Age (per 1 year older)	0.095	1.10 (10% ↑ risk/year)
Male Sex (1 = male)	0.35	1.42 × risk for males vs females
BMI (per 1 kg/m² higher)	0.02	1.02 (≈10% ↑ per +5 BMI)
Push-up Score (per +10 points)	–0.06	0.94
Squat Score (per +10 points)	–0.06	0.94
One-Leg Balance Score (per +10 points)	–0.06	0.94
Vertical Jump Score (per +10 points)	–0.05	0.95
Overhead Squat (fail vs pass)	0.262	2.20× if fail
Flexibility Score (per +10 points)	–0.07	0.93

Limitations of our current risk models:

Due to readily available data linking our specific test protocol and the calculated risks, we use assumptions and derivations to fuel our predictions. Thus, these coefficients and risk models are temporary and limited by the data in the literature. Once we possess more data using our exact testing protocol we will be updating our model.

This risk model is only an initial attempt that needs to be thoroughly tested and isn't intended to be the final model.

Also, due to the lack of data, our normalization approach for each test that we use to score each one from 0-100 is imperfect. We need a more rigorous normalization model for each of our tests to be able to score them more accurately across different user strata.

In the future we plan to switch from interpretable statistical approaches to ML-based interpretation which may point out correlations that our model can not accurately point out, once more data becomes available.

The ML-based approaches will likely be using the rawer form of data from the tests such as the the timing and depth of each rep, jump height etc. and considering them all at once in linking them to clinical outcomes as opposed to deriving scores for each test and assigning hazard ratios to each individual test and modeling them independently.

Since we are considering each metric in isolation for simplicity at the moment, and some correlations are found to be co-dependent in peer reviewed studies, our approach is only an imperfect approximation.

With a more robust model with codependence, or an ML-based approach– which we will most likely be using in the future, we aim to deliver clinically proven prediction methods, which is beyond our ability to do so at the moment.

Validation Strategy:

To evaluate the system in practice, we will collect a large, diverse dataset of participants performing the smartphone-based fitness test and track their health outcomes over time. Key plans for data collection include:

Sample Size and Power: We will perform sample size calculations to ensure the study is powered to detect significant improvements in prediction performance over traditional models. Prior external validations of CVD risk models have enrolled on the order of 10,000 participants to observe a few hundred cardiovascular events over ~5 years. Based on these benchmarks, we plan to recruit several thousand participants, aiming for several hundred CVD events and sufficient deaths to robustly compare model performance.

Population Demographics: We will recruit a broad, representative sample of adults in the target population for CVD prevention. Age range will focus on mid-life to older adults (e.g. 40–75 years), since CVD events and mortality outcomes are more frequent in this group. Younger adults will also be included to provide data on this population which is understudied due to the rarity of the events we are screening for, but a sufficient number of older participants will be included to ensure capture of events.

We will strive for a balanced sex distribution (approximately 50% women and 50% men) and geographic and ethnic diversity in the cohort.

To maximize generalizability, recruitment will span multiple regions and ethnic groups. By ensuring diversity, we can assess the tool's performance across subpopulations and avoid bias. We will document baseline characteristics (age, sex, ethnicity, etc.) and traditional risk factors (e.g. smoking status, blood pressure, cholesterol if available) so that we can later stratify results and compare against established risk scores.

ACF.Test Video Data Collection Protocol: Participants will perform the prescribed test in front of their smartphone camera using the ACF.Test app. To standardize data collection at scale, we have developed clear instructions and in-app guidance: for example, specifying how to position the smartphone, the space needed to exercise safely, and a step-by-step guide for the test movements.

The app includes real-time feedback or tutorials to ensure proper form. We also capture details about the timing and sequence of tests to enforce a consistent protocol. The raw video data is uploaded to a secure cloud server for analysis.

To verify adherence and data quality: (1) the app's computer vision algorithms automatically checks each recording for completeness (e.g. all required motions done, adequate lighting, camera angle) and flag any invalid tests; (2) during the validation phase a random sample of videos will undergo manual review by the research team to audit quality and protocol compliance.

All video data is time-stamped and logged, and metadata (device type, app version, any user prompts) is recorded to help identify any systematic issues in data collection.

Outcome Data Collection and Follow-Up: We will obtain clinical outcome data on each participant through a combination of active follow-up and passive health record linkage. Each participant will be followed for a multi-year period (up to 10 years or even beyond) to observe occurrences of CVD events and mortality.

With consent, we will link participants to external data sources for objective outcomes. For example, we will work with national health databases, electronic health record systems, and/or insurance claims.

Major CVD events are defined as follows: composite of non-fatal myocardial infarction, non-fatal stroke, or cardiovascular death. However we will aim to collect any clinically significant CVD event as well as major events. This is to ensure we have the data to not just predict, but intervene before other such events occur when we are using our system in the real world.

All-cause mortality will be captured from death registry data.

In conclusion, this testing and validation proposal provides a roadmap to rigorously evaluate the ACF.Test CVD and mortality risk scoring system in a real-world, ethically responsible manner.

By collecting comprehensive data from a large, diverse population, we will determine how well the new model performs relative to existing standards.

All these steps will be documented in a formal study protocol and carried out by a multidisciplinary team (data scientists, clinicians, ethicists etc.), ensuring that the validation of ACF’s risk scoring system is both scientifically rigorous and ethically sound.

Conclusion:

In conclusion, while the use of smartphone camera-based functional fitness tests for cardiovascular disease and mortality risk prediction is a step forward, no protocol and technique has been fully validated for predictive accuracy across demographic strata.

Our initial risk model has inherent limitations and has not undergone large-scale prospective validation, so any risk estimates should be interpreted with caution. We acknowledge these constraints and emphasize the need for further research and broad validation studies to establish the model's accuracy and generalizability. Only through rigorous, large-cohort evaluation can this approach be confirmed as a reliable addition to be deployed for large scale risk assessment.

Despite these caveats, integrating computer vision based functional fitness metrics into CVD and all-cause mortality prediction holds significant potential. Functional fitness is a well-known independent indicator of health outcomes, and low performance on simple physical tests correlates with higher mortality risk as demonstrated by a large volume of studies.

By supplementing (not replacing) traditional risk factors with objective fitness data, this approach could provide a more holistic risk profile for individuals, and one that can be used at negligible cost at large scale. Such an enriched model may improve the identification of high-risk patients beyond what conventional models achieve, ultimately contributing to more informed preventive strategies.

Looking ahead, the forthcoming ACF.train platform could synergistically enhance the impact of this risk model by translating assessments into actionable, individualized interventions.

ACF.train will be offering tailored fitness regimens based on each person's test outcomes, enabling targeted improvements in the areas of weakness identified by the functional tests. By coupling risk estimation with a personalized exercise program

In summary, although current evidence is preliminary for our approach, the combination of computer vision analytics for risk prediction and guided interventions like ACF.train illustrates a promising, forward-looking path for improving health and longevity.

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