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ORIGINAL ARTICLE
Artificial intelligence (machine learning, deep learning)

Association between gait video information and general cardiovascular diseases: a prospective cross-sectional study

Juntong Zeng [1,2,3,†], Shen Lin [1,2,3,4,5,†], Zhigang Li [6,7,†], Runchen Sun [1,2,3], Xuexin Yu [6,7], Xiaocong Lian [6,7], Yan Zhao [1,2,4,5], Xiangyang Ji [6,7,*], and Zhe Zheng [1,2,3,4,5,*]

[1]National Clinical Research Center of Cardiovascular Diseases, National Center for Cardiovascular Diseases, Fuwai Hospital, No. 167 North Lishi Road, Xicheng District, Beijing 100037, People's Republic of China; [2]State Key Laboratory of Cardiovascular Disease, National Center for Cardiovascular Diseases, Fuwai Hospital, No. 167 North Lishi Road, Xicheng District, Beijing 100037, People's Republic of China; [3]Chinese Academy of Medical Sciences and Peking Union Medical College, No. 9 Dongdansantiao, Dongcheng District, Beijing 100730, People's Republic of China; [4]Department of Cardiovascular Surgery, National Center for Cardiovascular Diseases, Fuwai Hospital, No. 167 North Lishi Road, Xicheng District, Beijing 100037, People's Republic of China; [5]Key Laboratory of Coronary Heart Disease Risk Prediction and Precision Therapy, Chinese Academy of Medical Sciences and Peking Union Medical College, No. 167 North Lishi Road, Xicheng District, Beijing 100037, People's Republic of China; [6]Department of Automation, Tsinghua University, Room 711A, Main Building, Haidian District, Beijing 100084, People's Republic of China; and [7]Beijing National Research Center for Information Science and Technology (BNRist), Tsinghua University, Haidian District, Beijing 100084, People's Republic of China

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Aims Cardiovascular disease (CVD) may not be detected in time with conventional clinical approaches. Abnormal gait patterns have been associated with pathological conditions and can be monitored continuously by gait video. We aim to test the association between non-contact, video-based gait information and general CVD status.

Methods and results Individuals undergoing confirmatory CVD evaluation were included in a prospective, cross-sectional study. Gait videos were recorded with a Kinect camera. Gait features were extracted from gait videos to correlate with the composite and individual components of CVD, including coronary artery disease, peripheral artery disease, heart failure, and cerebrovascular events. The incremental value of incorporating gait information with traditional CVD clinical variables was also evaluated. Three hundred fifty-two participants were included in the final analysis [mean (standard deviation) age, 59.4 (9.8) years; 25.3% were female]. Compared with the baseline clinical variable model [area under the receiver operating curve (AUC) 0.717, (0.690–0.743)], the gait feature model demonstrated statistically better performance [AUC 0.753, (0.726–0.780)] in predicting the composite CVD, with further incremental value when incorporated with the clinical variables [AUC 0.764, (0.741–0.786)]. Notably, gait features exhibited varied association with different CVD component conditions, especially for peripheral artery disease [AUC 0.752, (0.728–0.775)] and heart failure [0.733, (0.707–0.758)]. Additional analyses also revealed association of gait information with CVD risk factors and the established CVD risk score.

Conclusion We demonstrated the association and predictive value of non-contact, video-based gait information for general CVD status. Further studies for gait video-based daily living CVD monitoring are promising.

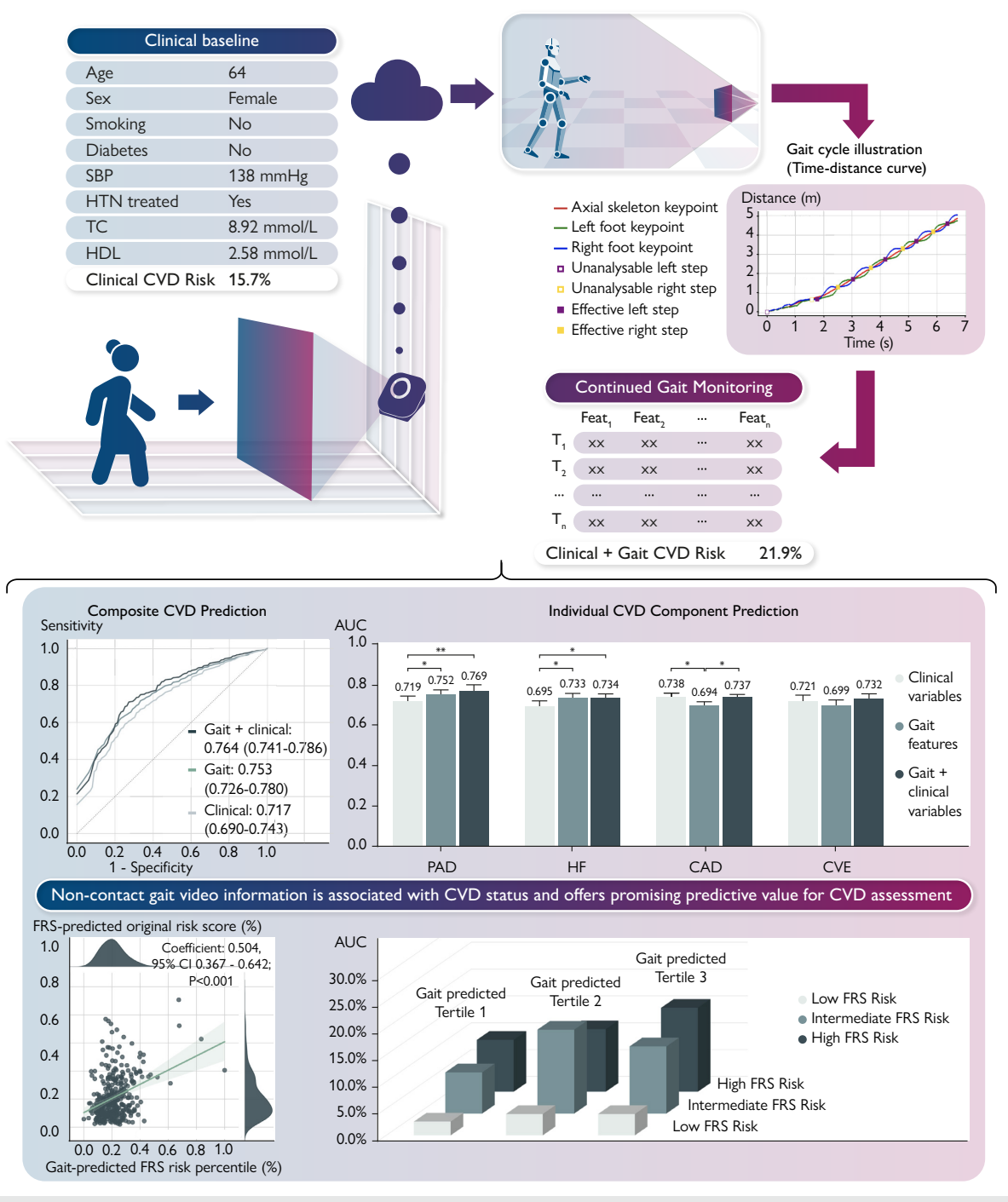
Lay summary We conducted a prospective cross-sectional study to investigate the association between video-based gait information and general cardiovascular disease (CVD) status, with findings suggesting the potential of non-contact, video-based gait information for continuous CVD monitoring and early detection:

- Gait video information extracted by advanced machine learning algorithms was well associated with general CVD status and demonstrated the predictive performance both significantly better and incremental to the conventional clinical risk factors.

* Corresponding author. Tel: +86 10 88396051, Fax: +86 10 88396051, Email: zhengzhe@fuwai.com (Z.Z.); Tel: +86 10 62792481, Fax: +86 10 62792481, Email: xyji@tsinghua.edu.cn (X.Y.)
†The first three authors contributed equally to the study.

- Among individual CVD components, gait information exhibited differential predictive value and feature contribution, with particularly noteworthy performance in predicting peripheral artery disease and heart failure.

Graphical Abstract



AUC, area under the receiver operating characteristic curves; CVD, cardiovascular diseases; HDL, high-density lipoprotein; HTN, hypertension; FRS, Framingham Risk Score; SBP, systolic blood pressure; TC, total cholesterol.

Keywords Cardiovascular disease • Gait • Heart failure • Peripheral artery disease • Framingham Risk Score • Machine learning

Introduction

Cardiovascular disease (CVD) is the leading cause of death worldwide and imposes significant burden on society.[1] Early prediction and risk stratification is a widely recognized strategy to improving patient outcomes for CVD.[2,3] Traditional clinical risk factors such as age, sex, smoking, hypertension, hyperlipidaemia, and diabetes have been commonly incorporated in multivariate models for estimating and stratifying CVD risk, with well-known examples like the Framingham Risk Score (FRS) general CVD prediction system.[4–6] Based on individuals' risk profile and presentations, clinicians decide on specific examinations to confirm diagnosis. However, patients with underlying chronic conditions, such as atherosclerotic cardiovascular disease (ASCVD), even being assessed as high risk, tend to have a slowly progressive course with subtle change overtimes that may not be easily detected until significant clinical manifestation presented.[7,8] Therefore, there is a need for a more dynamic and proactive monitoring approach for early detection of CVD.

In recent decades, gait analysis has gained increasing traction across various health-related domains, as it reveals a new dimension of biological information that critically reflects human mobility, physical function, general health status, as well as underlying pathological states.[9–11] Many quantitative gait analyses have established evidence linking abnormal gaits with various cardiovascular risk factors,[12–14] comorbidities,[15–18] and prognosis.[19–21] However, no study has directly investigated the association between gait information and the presence of underlying CVD status. Moreover, existing gait analysis were limited in two major aspects:[10,22–24] (i) predominantly utilizing the few overly simplified gait metrics (e.g. gait speed) with limited information volume to capture gait information and (ii) often relying on specialized equipment for gait data acquisition that is either expensive and rarely accessible in practices (e.g. laboratory-based motion capture systems) or requires continuous close contact but with limited gait information (e.g. wearable devices). Recent progress in the computer vision field with the advent of artificial intelligence (AI)/machine learning (ML) technology has led to an increasing popularity of the video-based approach to gait analysis, which could not only offer comprehensive gait information but also is relatively convenient to operate.[9,23,25–27]

Thus, we hypothesize that human gait video may contain CVD-relevant information, and, therefore, the aim of the present study is to investigate the potential association between the information extracted from gait video and the underlying general CVD status.

Methods

Study design and participants

The current study included individuals participating in a single-centre, prospective, cross-sectional study (ClinicalTrials.gov Identifier: NCT04941560). Briefly, adult individuals suspected of CVD and undergoing confirmatory examinations were invited to participate in the study. A series of non-contact procedures were conducted prior to CVD assessment to capture several forms of biophysiological information, including gait video, thermography, and photography. The current study reported the findings of the gait analysis sub-study (detailed inclusion and exclusion criteria of the overall study in Supplementary material online, *Method S1*). This study complied with the Declaration of Helsinki, and the current data used were approved by the institutional review board at Fuwai Hospital. Informed consents were obtained from all eligible patients, with permission to use their gait videos, as well as required medical record data, for research-only, de-identified analysis. Our study followed the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) reporting guideline (see Supplementary material online, *Table S1*).[28]

Data collection

Baseline information, including participants' presenting symptoms, lifestyles, socioeconomic status, medical and family history, and medication usage, was collected by trained clinical researchers. Gait video recording was conducted in two pre-specified real-world, open-space corridors en route to two designated examination rooms, respectively. A Microsoft Kinect camera device with the depth sensor (Microsoft, WA, USA) was placed at the end of each corridor. Participants were instructed to walk in their usual pace straight towards the camera and were recorded from the same staring point 5 m away from the camera until in near contact. Further demographic details, clinical history, baseline blood biochemistry results, and confirmatory CVD workup findings were obtained by reviewing participants' electronic medical records post-procedure.

Gait data preparation and cardiovascular disease labelling

For each participant, one gait video was recorded and underwent preparation before being included in the final analyses of the current study. The preparation pipeline consisted of the following steps:

(1) Initial non-walking frame removal: the initial frames at the beginning of the gait videos were manually inspected to remove the non-walking segments where participants were preparing and not yet beginning to walk at the start point.
(2) Skeleton keypoint data transformation: the post-edited gait video was then transformed into skeleton keypoint data using the official Microsoft Azure Kinect software development kit (SDK). The Body Tracking SDK contains established computer vision-based AI tools that enables automatically detection of the walking human body and tracking 32 skeleton keypoints, including keypoints at the head, nose, neck, thoracic spine, lumbar spine, pelvis, and bilateral keypoints at the eyes, ears, clavicles, shoulders, elbows, wrists, hands, fingertips, thumbs, hips, knees, ankles, and feet. The Body Tracking SDK outputted a JavaScript Object Notation (JSON) format file that contained the three-dimensional coordinates for each keypoint of every video frame (see Supplementary material online, *Method S2*).
(3) Gait cycle detection and examination: with the temporal and spatial information from the skeleton keypoint data, an algorithm was developed to automatically segment the gait cycle. A gait cycle is defined as the interval between two subsequent same-side (e.g. left) foot contacts to the ground, whose length equals to the sum of the pair of two opposite-side steps. For each participant, the post-segmented skeleton keypoint data were then visually illustrated as the relationship between the walking time and walking distance of keypoints. The gait cycle segmentation was inspected visually, and at least one effective gait cycle was deemed as the minimal requirement for inclusion to the final analyses for the present study (see Supplementary material online, *Method S3*).

The main target of interest in the current study is the presence of the composite general CVD status, which encompassed any of the following component conditions: (i) coronary artery disease (CAD), defined as any major epicardial coronary artery stenosis $\geq$ 70% or left main artery stenosis $\geq$ 50% evidenced by invasive coronary angiography (ICA) or coronary computed tomography angiography (CCTA); (ii) peripheral artery disease (PAD), defined as documented diagnosis of PAD or index ankle–brachial index (ABI) $\leq$ 0.9 with suggestive symptoms or signs; (iii) heart failure (HF), defined as symptoms or signs due to structural and/or functional cardiac abnormality plus either elevated natriuretic peptide levels (BNP $\geq$ 100 pg/mL or NT-proBNP $\geq$ 300 pg/mL) or cardiogenic pulmonary or systemic congestion evidence from imaging or haemodynamic examinations;[29] and (iv) cerebrovascular event (CVE), defined as documented diagnosis or index incidence of ischaemic stroke, haemorrhagic stroke, or transient ischaemic attack.

Gait information extraction

Following detection and segmentation of gait cycles from the processed skeleton keypoint data, the effective gait cycle data of the included participants were used for gait information extraction. Four main categories of gait feature were extracted, including the distance, duration, velocity, and variability domain, resulting in a total of 30 gait features (see Supplementary material online, *Table S2*, for a complete feature list and description).

Gait information for cardiovascular disease prediction and feature contribution

To investigate the association between gait information and underlying CVD, we assessed both the overall performance and individual feature

contribution of gait information for CVD status prediction. Specifically, we developed and evaluated CVD prediction models using five repetitions of five-fold cross-validation with random shuffling. We employed the XGBoost algorithm, a gradient boosted decision tree ML approach,[30] as the underlying prediction model structure. The aforementioned 30 gait features and/or the 8 clinical variables included in the FRS general CVD prediction system[4] (i.e. age, sex, smoking, diabetes mellitus, systolic blood pressure, anti-hypertension treatment, total cholesterol, and high-density lipoprotein) were utilized as input variables to develop 3 types of models (i.e. the clinical model, the gait feature model, and the clinical + gait feature model) in our current data set. The clinical model based on the eight clinical variables served primarily as a baseline performance measure of conventional clinical information in assessing CVD status. The choice of clinical variables was derived from the FRS general CVD prediction system as it is a well-recognized prediction system with the most similar target disease to our current study. The same modelling approach and variables were used to develop prediction models for each of the individual CVD component conditions (i.e. CAD, PAD, HF, and CVE), respectively. To better understand how gait information contributed to the prediction of the composite general CVD status and its individual component conditions, we leveraged the in-built feature importance functionality of the tree-based ML models to obtain importance rankings of individual gait features. These importance scores were assigned to each feature based on their contributions to the overall model performance.

Understanding the association between gait information and cardiovascular disease risk status

To further understand and support the association between the extracted gait information and the CVD status, we further conducted a series of additional analyses. These include (i) analysing the difference in gait features between different CVD case vs. non-case participants; (ii) exploring the value of gait information in predicting traditional CVD risk factors; (iii) assessing the association between gait information and the original FRS, which represent individual participants' future general CVD risk; and (iv) evaluating the contribution of gait features in predicting the FRS risk category, as well as their add-on potential in further stratifying CVD risk groups on top of the FRS.

Statistical analysis

Continuous variables were presented with mean and standard deviation (SD) or median and interquartile range (IQR), and categorical variables with number and percentage. Continuous variables were compared using Student's *t*-test or the Wilcoxon rank-sum test, as appropriate. Categorical variables were compared using the χ^2 test or Fisher's exact test. The association between gait information and the composite or individual CVD component conditions was primarily assessed for the overall predictive performance using the area under the receiver operating characteristic curve (AUC) with 95% confidence interval (CI). To compare AUC between models based on clinical variables, gait features, or the combined, the Delong method was used. The continuous net reclassification index (NRI) and its 95% CIs were also calculated and compared with bootstrapping to further assess the incremental value of gait features in addition to clinical variables. Several additional sensitivity and/or exploratory analyses were performed, including (i) assessing the model performance after rebalancing for the general CVD status composition, (ii) examining the model performance in differentiating participants with individual CVD component conditions from healthy controls (i.e. the participants without any CVD component conditions), and (iii) exploring the potential of gait information in predicting subclinical stroke (defined as the presence of imaging evidence of a brain infarct lesion in addition to the absence of manifestations attributed to a potential stroke). The rebalancing for the general CVD status in each cross-validation split was achieved with the over-sampling method of 'SMOTENC' from the imbalanced-learn package (v 0.9.1) relying on scikit-learn. All statistical comparisons were two-sided, with statistical significance defined as $P < 0.05$, without adjustment for multiple comparisons. Python v3.9.12 was used for data preprocessing and model development, and R v 4.0.3 (R Foundation for Statistical Computing, Vienna, Austria) was used for plotting and statistical analysis.

Results

Study participant overview

Between 6 September 2021 and 10 February 2023, a total of 460 eligible adult participants undergoing ASCVD evaluation were enrolled in the overall study. For the current gait sub-study, one participant failed to complete the gait video recording procedure due to equipment malfunction. Of the remaining 459 participants' recorded gait videos undergoing preparation, 107 gait videos were not successfully transformed into analysable skeleton keypoint-based gait cycle data, with 102 due to real-world environmental factors such as lighting-related overexposure or reflection, and interference by other pedestrians or moving objects entering the capturing frame. Additionally, another five gait videos were excluded due to insufficient (<1) complete effective gait cycles for feature extraction after skeleton keypoint transformation. Therefore, a total of 352 participants' gait videos were effectively processed and extracted for gait features and included in the final analysis of the present study (*Figure 1*). Among this final data set, the mean age was 59.4 (SD 9.8) and 89 individuals (25.3%) were female. A total of 62.5% had hypertension, 82.4% for hyperlipidaemia, 27.6% with diabetes, and 52.3% with smoking history. A total of 293 participants (83.2%) were confirmed to have at least 1 CVD, including 233 (66.2%) with CAD, 51 (14.5%) with PAD, 98 (27.8%) with HF, and 62 (17.6%) with CVE (*Table 1*).

Comparison of gait features between different cardiovascular disease cases and non-cases

Supplementary material online, *Table S3*, summarized gait features that were significantly different between participants with and without different CVDs in either the unadjusted or adjusted analyses. In the unadjusted analyses, a total of 16 gait features were significantly different between different CVD case and non-case groups (*Figure 2*). For the composite general CVD status, the mean velocity was significantly lower in participants with the composite CVD (1.094 m/s, SD 0.276) than those without (1.184 m/s, SD 0.295) ($P = 0.024$), and gait stability ratio (GSR) was significantly higher in participants with the composite CVD (6.381 steps/m, SD 3.876) than those without (5.332 steps/me, SD 2.871) ($P = 0.049$). For HF, six gait features were significantly different, including shorter mean stride length, mean step length, mean left and right stride length, and mean left step length, as well as longer mean left stride time, in participants with HF. For PAD, seven features were significantly different, including higher GSR, shorter mean stride length, mean step length, mean left and right stride length, and mean right step length, as well as slower mean velocity, in participants with PAD. For CVE, only one feature, mean right step length, was significantly different and lower in CVE participants. After adjustment for age, sex, and height, 12 of the aforementioned 16 gait features remain significantly different between the different CVD case and non-case groups, and an additional gait feature, the stride asymmetry, was shown to be statistically different between HF (−1.708, SD 8.465) vs. non-HF (−0.269, SD 5.953) group ($P = 0.046$).

Performance of gait information and/or clinical variables in predicting the composite general cardiovascular disease status and individual cardiovascular disease component conditions

The different model performance in predicting the composite general CVD status in the validation sets under the five-repeated five-fold

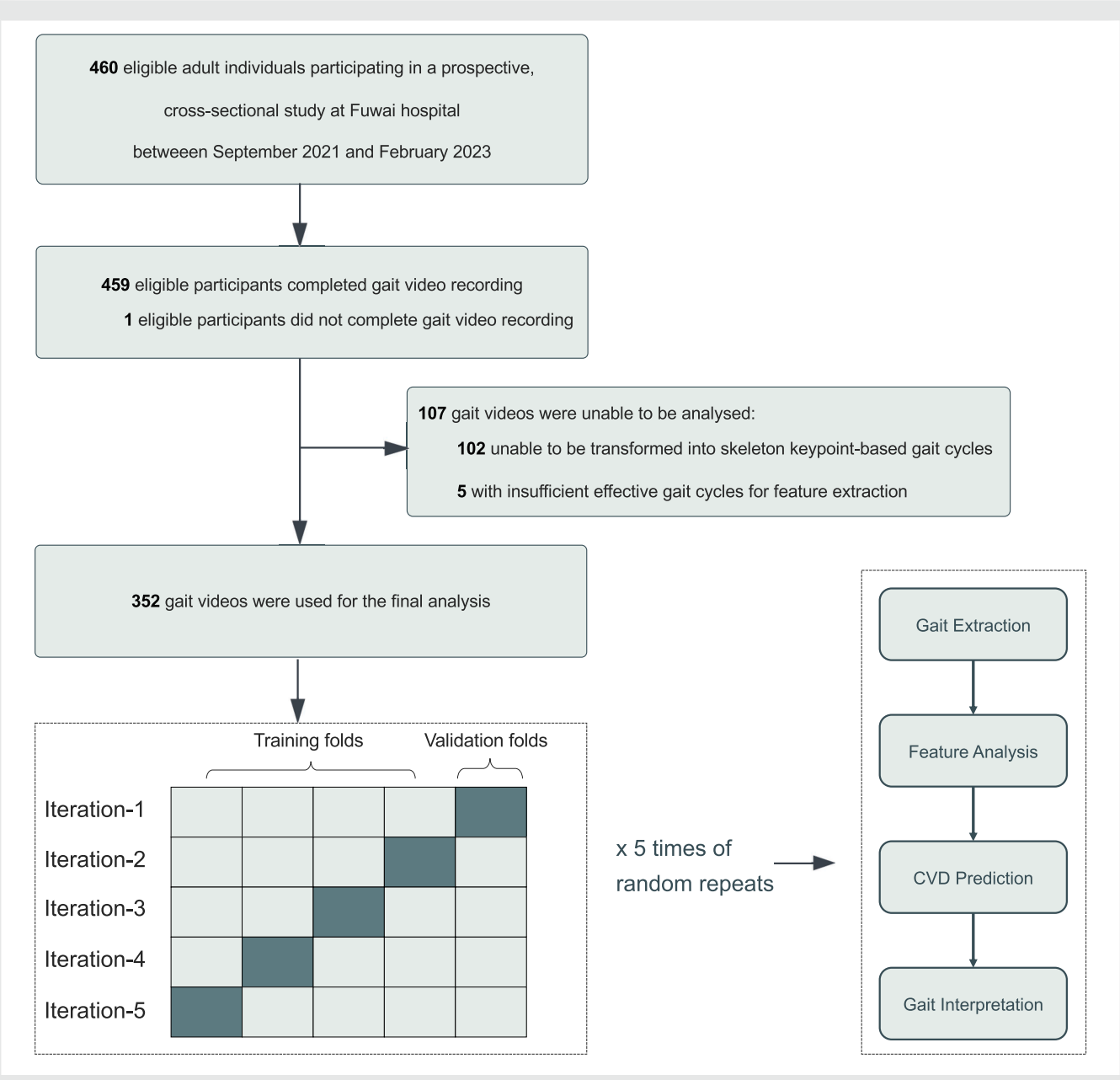


Figure 1 Flowchart of the data set and study design. CVD, cardiovascular diseases.

cross-validation design is summarized in *Table 2* and *Figure 3A*. In comparison with the baseline clinical model (AUC 0.717, 95% CI 0.690–0.743), the gait feature model exhibited significantly better performance (AUC 0.753, 95% CI 0.726–0.780) ($P = 0.024$). Furthermore, the incorporation of gait features with clinical variables in the combined model led to a further significant improvement in AUC (0.764, 95% CI 0.741–0.786) ($P = 0.002$) and the continuous NRI 0.628 (0.497–0.759), compared with the baseline clinical model alone. Overall similar trends of improved model performance were also observed in threshold-dependent metrics when comparing gait features to clinical variables.

Table 2 and *Figure 3B* summarize the model performance for gait features, clinical variables, and the combined in predicting individual components of the composite CVD. Notably, for both PAD and HF, gait features demonstrated significantly better model performance [AUC 0.752, 95% CI (0.728–0.775) for PAD; AUC 0.733, 95% CI (0.707–0.758) for HF] compared with clinical variables [AUC 0.719, 95% CI (0.695–0.744), $P = 0.020$, for PAD; AUC 0.695, 95% CI (0.669–0.721), $P = 0.043$ for HF]. Incorporating gait features with the clinical variables also led to significant further improvements [AUC 0.769, 95% CI (0.737–0.801), $P = 0.004$, for PAD; AUC 0.734, 95% CI (0.712–0.756), $P = 0.036$, for HF]. However, when predicting CAD or CVE, gait features alone or in combination with clinical variables did not demonstrate significantly better model performance in comparison with clinical variables alone [AUC 0.738, 95% CI (0.716–0.760) for CAD; AUC 0.721, 95% CI (0.693–0.750) for CVE].

Analysis of gait feature contribution to cardiovascular disease prediction

Given the significantly better performance of gait features in predicting the composite CVD, PAD, and HF, further feature importance analysis was performed to better understand how gait feature contributed to

Table 1 Baseline characteristics

	Overall ($n = 352$)
Birth region, *n* (%)	
North	327 (92.9)
South	25 (7.1)
Han ethnicity, *n* (%)	308 (87.5)
Education level, *n* (%)	
Less than high school	136 (38.6)
High school	103 (29.3)
College	107 (30.4)
Post-graduate or above	6 (1.7)
Work time, *n* (%)	
Unemployed or retired	231 (65.6)
<8 h/day	49 (13.9)
8–10 h/day	45 (12.8)
≥10 h/day	27 (7.7)
Sedentary work[a], *n* (%)	69 (19.6)
Diet and lifestyle	
Alcohol use[b], *n* (%)	111 (31.5)
Meat intake[c], *n* (%)	28 (8.0)
Fastfood consumption[d], *n* (%)	2 (0.6)
Exercise[e], *n* (%)	
Never	106 (30.1)
1–2 times/week	103 (29.3)
≥3 times/week	143 (40.6)
Age, mean (SD), years	59.4 (9.8)
Female, *n* (%)	89 (25.3)
Smoking, *n* (%)	184 (52.3)
BMI, mean (SD)	25.6 (3.1)
Obesity, *n* (%)	72 (20.5)
Metabolic syndrome, *n* (%)	124 (35.2)
Hypertension, *n* (%)	220 (62.5)
Hyperlipidaemia, *n* (%)	290 (82.4)
Diabetes mellitus, *n* (%)	97 (27.6)
COPD, *n* (%)	6 (1.7)
Systolic blood pressure, mean (SD), mmHg	134.5 (17.2)
LVEF, mean (SD)	63.0 (6.4)
eGFR, mean (SD), mL/min/1.73 m^2	89.8 (14.8)
Fast glucose, mean (SD), mmol/L	6.4 (2.1)
Total cholesterol, mean (SD), mmol/L	4.2 (1.2)
HDL, mean (SD), mmol/L	1.2 (0.3)
Triglyceride, mean (SD), mmol/L	1.7 (1.8)
Anti-hypertension medications, *n* (%)	193 (54.8)
Statin, *n* (%)	170 (48.3)
Peripheral artery disease, *n* (%)	51 (14.5)
Heart failure, *n* (%)	98 (27.8)
Coronary artery disease, *n* (%)	233 (66.2)
Cerebrovascular events, *n* (%)	62 (17.6)
Composite cardiovascular diseases[f], *n* (%)	293 (83.2)

BMI, body mass index; COPD, chronic obstructive pulmonary disease; eGFR, estimated glomerular filtration rate; HDL, high-density lipoprotein; LVEF, left ventricular ejection fraction; SD, standard deviation.
[a]Sedentary work is defined as sitting while at work ≥6 h/day.
[b]Alcohol use is defined as >2 times/week for >1 year.
[c]Meat intake is defined as >2 times/week, >300 g/time.
[d]Fastfood intake is defined as >4 times/week.
[e]Exercise is defined as aerobic exercise > 1 h/time.
[f]Composite cardiovascular disease included any of the following: peripheral artery diseases, heart failure, coronary artery disease, and cerebrovascular events.

prediction of these conditions. *Figure 4A* outlined the top 20 gait features based on their mean relative feature importance. For predicting the composite CVD, the three most influential features were all SD-related variables, including the SD of right step length, left stride time, and overall step length. In PAD prediction, the top three features comprised mean stride length, mean left stride time, and SD of overall stride time, while for HF, the three most significant features included mean left stride length, GSR, and mean right stride length.

When examining the relative portion of contribution across the four primary feature domains *Figure 4B*, variability domain features (e.g. SD-related variables) constituted the largest proportion (51.4%), followed by distance domain (e.g. length-related variables, 21.4%), duration domain (e.g. time-related variables, 16.8%), and the velocity domain (e.g. mean velocity and cadence variables, 10.4%). Overall, similar patterns of feature importance proportion were observed for both HF and PAD, although the distance domain contributed a relatively larger proportion in predicting HF (32.4%) and PAD (31.6%) compared with 21.4% in predicting composite CVD. Furthermore, in PAD prediction, the velocity domain displayed a relatively higher proportion in comparison with the duration domain (10.5% vs. 8.4%), different from the patterns observed for composite CVD and HF (10.4% vs. 16.8% for composite CVD and 9.2% vs. 14.7% for HF).

To better understanding the potential underlying mechanism of gait information in predicting CVD, *Table 3* presented the overall performance of gait information in predicting important risk factors that are traditionally considered to be highly associated with CVD.

Gait information in association with the original Framingham Risk Score

Table 4 reported the performance of gait information in predicting both the three-level FRS risk category (low, intermediate, and high risk) [AUC 0.705, 95% CI (0.687–0.723)] and the binary high FRS risk category (high risk and non-high risk) [AUC 0.691, 95% CI (0.674–0.708)]. Supplementary material online, *Table S4*, summarized the gait features that were significantly different between participants of high and non-high FRS risk category in either the unadjusted or adjusted analyses. Supplementary material online, *Figure S1*, depicted the gait feature importance in contributing the FRS category prediction. *Table 4* and *Figure 5A* jointly demonstrated the significant association between the gait-predicted FRS value and the original FRS value, with association coefficient = 0.504, 95% CI (0.367–0.642) ($P < 0.001$). Furthermore, *Figure 5B* depicted a potential two-factor risk grouping plot for the prevalence of composite CVD status stratified by both FRS risk categories and gait-predicted FRS tertile.

Additional sensitivity and/or exploratory analyses

Supplementary material online, *Table S5*, presented the results of the experiment involving rebalancing for the composite CVD status in each cross-validation split, with result findings overall following a similar

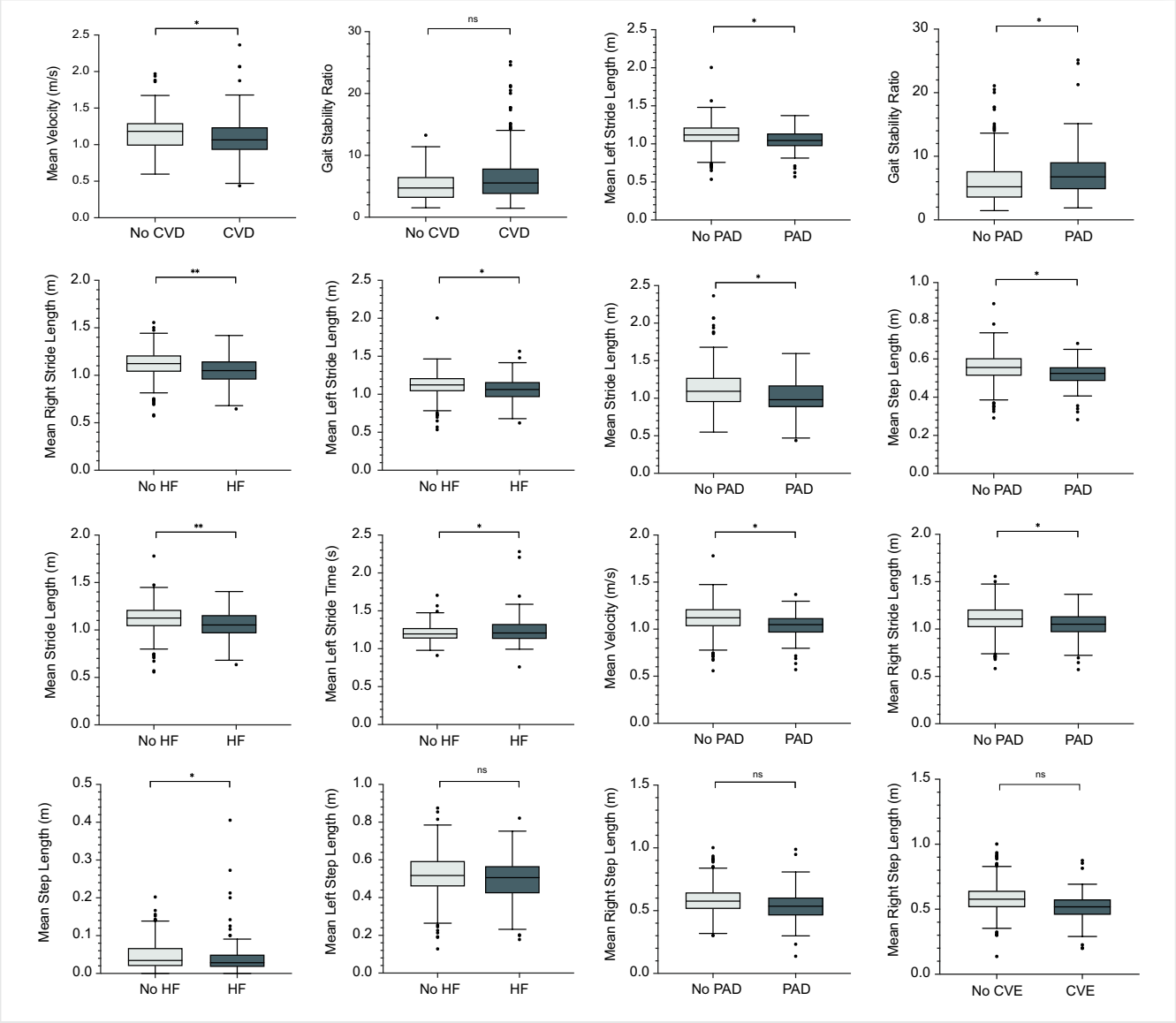


Figure 2 Comparison of gait features between different CVD case and non-case. Gait features with statistically significant difference (unadjusted *P*-value < 0.05) between different CVD case vs. non-case participants were presented. The asterisks here refer to the adjusted *P*-value for between-group comparison, with 'ns' indicating between-group comparison *P*-value > 0.05, **P*-value < 0.05, and ***P*-value < 0.01. CVD, cardiovascular diseases; HF, heart failure; PAD, peripheral artery diseases.

trend as the original unbalanced experiments. Supplementary material online, *Table S6*, reported the performance of gait information in differentiating participants with individual CVD component conditions from healthy controls, overall consistent with the results of the case vs. non-case experiment above. Finally, Supplementary material online, *Table S7*, showed the predictive value of gait information in differentiating subclinical stroke from healthy controls, subclinical stroke and/or clinical CVE from healthy controls, and subclinical stroke and/or clinical CVE participants from non-case participants, respectively. Supplementary material online, *Figure S2*, also depicted the interpretation of the importance of gait features for predicting subclinical stroke.

Discussion

In this study, we demonstrated that gait features extracted from non-contact gait video were well associated with and predictive for general CVD status, especially for PAD and HF. Prediction models based on gait features performed better than those based on conventional clinical risk factors and with incremental prediction value when further incorporated into the traditional prediction models. The predictive value of gait information for CVD assessment was further supported by its association with traditional CVD risk factors and the original FRS risk profile, as well as its potential add-on value for further CVD risk stratification.

This is the first study to directly investigate the association between gait information and presence of general CVD status. Previous studies have provided substantial evidence linking human gait information with cardiovascular adverse event risk or overall prognosis,[19–21] primarily grounded in the well-established association between abnormal mobility and deteriorating physical function.[31–36] Notably, frailty and sarcopenia, two common pathophysiological conditions indicative of declining physical function, often manifest as abnormal gait patterns and have been linked to the underlying atherosclerotic process and

Table 2 Performance of models with gait features and/or conventional clinical variables in predicting the composite general cardiovascular disease status and the individual component conditions

Performance metrics	Clinical models[a]	Gait feature models	Clinical + gait models	*P*-value
Composite general CVD status				
CVD–AUC	Ref: 0.717 (0.690–0.743)	0.753 (0.726–0.780)	0.764 (0.741–0.786)	FRS vs. gait: 0.024 FRS vs. FRS + gait: 0.002
CVD–continuous NRI	Ref.	—	0.628 (0.497–0.759)	<0.001
At prediction threshold when (Sen + Spe) $_{max}$				
CVD–sensitivity	0.676 (0.599–0.753)	0.709 (0.655–0.762)	0.727 (0.681–0.773)	—
CVD–specificity	0.749 (0.685–0.813)	0.798 (0.739–0.857)	0.782 (0.734–0.831)	—
CVD–accuracy	0.689 (0.633–0.744)	0.724 (0.685–0.763)	0.736 (0.703–0.769)	—
CVD–F1 score	0.764 (0.706–0.822)	0.802 (0.766–0.838)	0.815 (0.783–0.846)	—
CVD–PPV	0.934 (0.919–0.948)	0.950 (0.936–0.964)	0.944 (0.931–0.958)	—
CVD–NPV	0.362 (0.318–0.405)	0.380 (0.341–0.418)	0.382 (0.352–0.411)	—
At prediction threshold when Sen ≈ 0.80				
CVD–sensitivity	0.795 (0.765–0.825)	0.820 (0.796–0.843)	0.795 (0.781–0.810)	—
CVD–specificity	0.525 (0.444–0.606)	0.521 (0.433–0.610)	0.619 (0.559–0.679)	—
CVD–accuracy	0.748 (0.727–0.769)	0.768 (0.752–0.784)	0.764 (0.750–0.779)	—
CVD–F1 score	0.838 (0.822–0.854)	0.854 (0.842–0.865)	0.848 (0.837–0.859)	—
CVD–PPV	0.893 (0.876–0.910)	0.896 (0.878–0.913)	0.911 (0.895–0.927)	—
CVD–NPV	0.343 (0.310–0.375)	0.362 (0.327–0.396)	0.373 (0.347–0.399)	—
Individual CVD component conditions				
PAD–AUC	Ref: 0.719 (0.695–0.744)	0.752 (0.728–0.775)	0.769 (0.737–0.801)	FRS vs. gait: 0.020 FRS vs. FRS + gait: 0.004
HF–AUC	Ref: 0.695 (0.669–0.721)	0.733 (0.707–0.758)	0.734 (0.712–0.756)	FRS vs. gait: 0.043 FRS vs. FRS + gait: 0.036
CAD–AUC	Ref: 0.738 (0.716–0.760)	0.694 (0.672–0.717)	0.737 (0.720–0.754)	FRS vs. gait: 0.019 FRS vs. FRS + gait: 0.917
CVE–AUC	Ref: 0.721 (0.693–0.750)	0.699 (0.673–0.725)	0.732 (0.706–0.757)	FRS vs. gait: 0.301 FRS vs. FRS + gait: 0.294

AUC, area under the receiver operating characteristic curve; CAD, coronary artery disease; CVE, cerebrovascular events; CVD, cardiovascular diseases; CI, confidence interval; FRS, Framingham Risk Score; HF, heart failure; NPV, negative predictive value; NRI, net reclassification index; PAD, peripheral artery diseases; PPV, positive predictive value; Ref, reference; Sen, sensitivity; Spe, specificity.
[a]FRS model indicates the multivariate model fitted based on the original FRS variables in our current data.

poor prognosis.[17,37–41] Therefore, these two conditions might act as the potential mediators and explain the currently identified association between gait information and general CVD status.

Varied performance of gait features in predicting individual CVD component conditions was observed and aligned with pathophysiological understanding. Although different CVD components share common pathological mechanisms (e.g. the underlying atherosclerosis pathological pathway), differences in their clinical presentations likely contributed to the varied strength of associations observed between clinical or gait variables and specific cardiovascular conditions. In the current study, difference in predictive value from gait features and conventional clinical variables was observed for different CVD component conditions. Gait features exhibited particularly promising potential in predicting PAD and HF, conditions where symptoms and signs, such as claudication and abnormal ABI in PAD[42] or decreased physical mobility and poorer performance in walk tests in HF, are prominently manifested during walking.[43] Extensive evidence also supports both the predictive and prognostic value of abnormal gait characteristics for these two conditions.[44,45] In contrast, cardiovascular conditions such as CAD appeared to be more closely associated with conventional clinical variables that are more often considered as traditional ASCVD risk factors. This observation, to some degree, aligns with our clinical understanding that unless significant ischaemic symptoms manifest during physical exertion, gait-related changes may not be as apparent as those seen in PAD or HF. Furthermore, there is also relatively limited existing evidence directly linking gait information with CAD. Thus, the current findings of the differential association between gait information and CVD component conditions may suggest the necessity and opportunities for developing more disease-specific CVD assessment tools with potential to leverage gait information more effectively, catering to the distinct characteristics and clinical manifestations of specific cardiovascular conditions.

The present findings suggest promising clinical application for CVD assessment. In practice, clinical prediction systems are frequently used to evaluate disease risk based on traditional clinical variables of demographics, history, laboratory tests, and at times, imaging. However, due to the slow and subtle progress of CVD course and the accessibility constraints of these clinical variables, this approach is more often used only for baseline risk estimation and unlikely to be re-assessed frequently, resulting in relatively static and delayed CVD detection.[7,8,46–48] Modern gait analysis has significantly expanded our capacity to more comprehensively characterize human gait function,

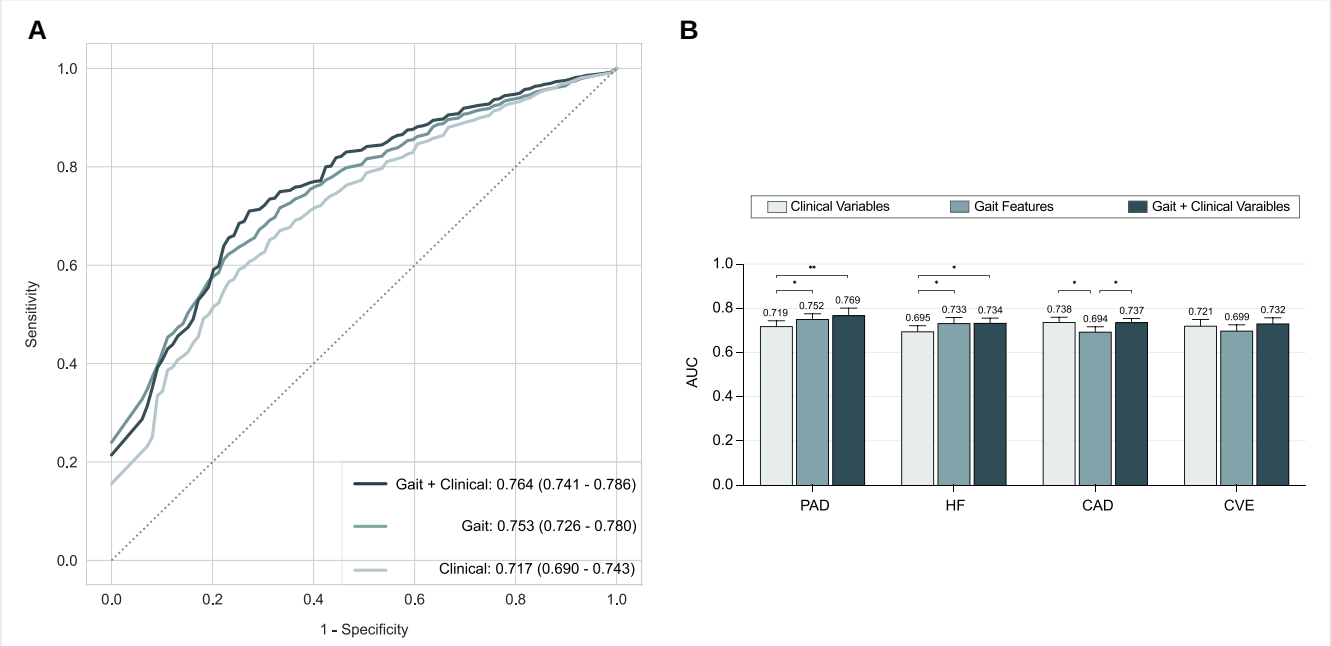


Figure 3 Performance of models of gait features and/or conventional clinical variables in predicting the composite general CVD status and its individual component conditions. (*A*) Area under the receiver operating characteristic curve (AUC) of different models in predicting the composite general CVD status. (*B*) AUC of different models in predicting individual CVD component conditions; *P-value < 0.05, **P-value < 0.01. AUC, area under the receiver operating characteristic curves; CAD, coronary artery disease; CVD, cardiovascular diseases; CVE, cerebrovascular events; HF, heart failure; PAD, peripheral artery diseases.

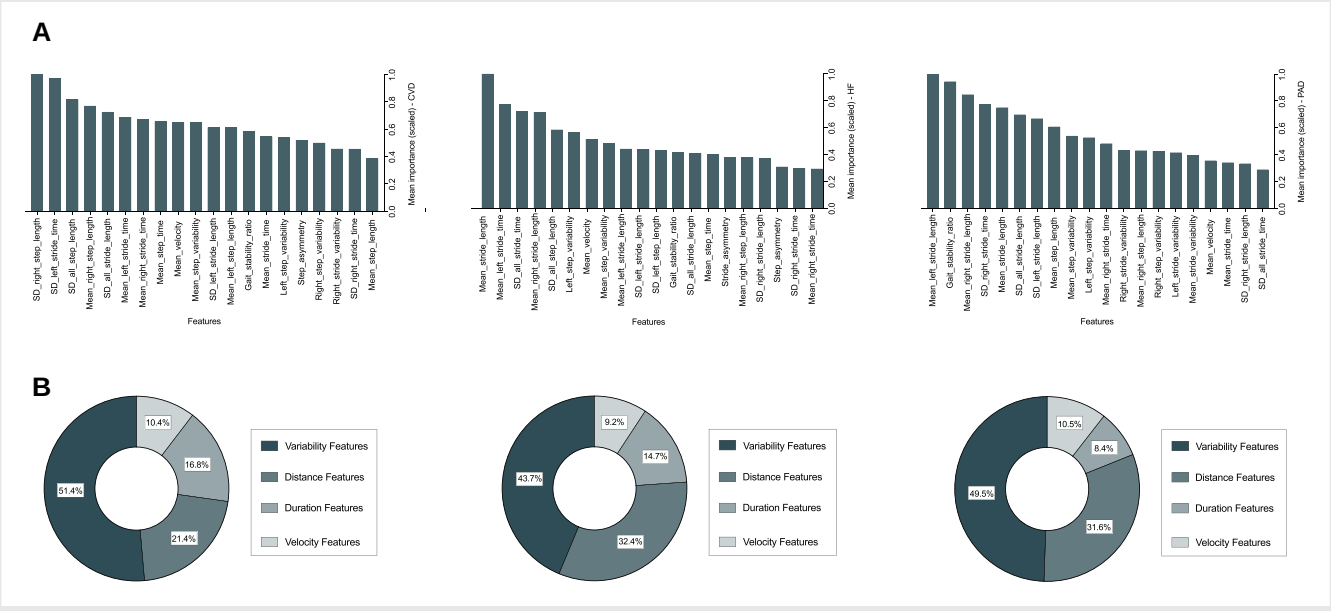


Figure 4 Gait feature contribution in predicting the composite CVD, HF, and PAD. (*A*) Top 20 important gait features in predicting the condition of interest. (*B*) Proportions of the importance makeup from different gait feature domains in predicting the condition of interest; CVD, cardiovascular diseases; HF, heart failure; PAD, peripheral artery diseases; SD, standard deviation.

allowing the use of biophysiological gait information beyond traditional clinical knowledge for disease assessment.[22,23,26] In the present study, we proposed and developed a pipeline for the gait video-based general CVD status assessment, which encompassed gait video capturing, data pre-processing that enabled a novel algorithm-based automatic gait cycle segmentation specific for three-dimensional gait video data, gait

Table 3 Gait features in predicting traditional atherosclerotic cardiovascular disease risk factors

Traditional CVD risk factors	AUC (95% CI)	MAE (95% CI)
Male	0.752 (0.728–0.775)	—
Elderly (≥65 years old)	0.711 (0.686–0.736)	—
Smoking	0.693 (0.674–0.713)	—
Hyperlipidaemia	0.733 (0.708–0.758)	—
Hypertension	0.668 (0.643–0.694)	—
Diabetes mellitus	0.700 (0.676–0.724)	
Obesity	0.722 (0.692–0.751)	—
BMI	—	2.369 (2.283–2.455)
LVEF	—	4.367 (4.192–4.542)

AUC, area under the receiver operating characteristic curve; BMI, body mass index; CVD, cardiovascular diseases; CI, confidence interval; LVEF, left ventricular ejection fraction; MAE, mean absolute error.

Table 4 Gait features in predicting the original Framingham Risk Score

Prediction target	AUC (95% CI)
FRS category (three-level: low/intermediate/high risk)[a]	0.705 (0.687–0.723)[b]
FRS category (binary: non-high/high risk)[a]	0.691 (0.674–0.708)

Correlation	Coefficient (95% CI)	*P*-value
Gait-predicted FRS ~ original FRS	0.504 (0.367–0.642)	<0.001

AUC, area under the receiver operating characteristic curve; CI, confidence interval; FRS, Framingham Risk Score; MAE, mean absolute error.
[a]High FRS risk ≥ 20% vs. non-high FRS risk < 20% (including intermediate FRS risk 7.5–20% and low FRS risk < 7.5%).
[b]AUC for micro-averaging one-vs.-rest multi-class AUC.

feature extraction, and prediction model training and interpretation. Importantly, the current proposed video-based gait analysis approach could provide such gait information in a non-contact, passive, and potentially much more practical manner than highly specialized laboratory-based motion capturing systems or wearable device-based gait analysis approaches used in many existing studies.[22,24,27] When deployed in the appropriate real-world settings, such approach may represent as a new paradigm of CVD monitoring that allows continuous and more dynamically updated risk assessment compared with the current relatively static 'watch-and-wait' strategy based on conventional clinical assessment. This could hold particular implications if utilized in environments that are less healthcare facility-centric but more reflective of an individual's daily status, such as long-term living facilities, nursing homes, or regular home settings (*Graphical Abstract*).[49] Specifically, the continuously monitored gait information in daily living space may capture subtle and progressive gait changes—changes that may be difficult to detect in regular clinical visits but related to underlying CVD status and could be integrated with the conventional clinical risk assessment to further refine existing disease risk assessment, potentially facilitating earlier CVD detection. However, it is also important to consider the privacy concern when deploying such non-contact, video-based health monitoring systems in daily living space. Currently, there is a growing field of research on privacy-preserving techniques and solutions to help balance the benefits of such non-contact monitoring with the privacy of the user.[49]

Several limitations should be acknowledged in the present exploratory study. Firstly, the relatively small sample size drawn from a single centre may have constrained the generalizability of the identified association between gait video information and general CVD status. Although we have conducted 5-time repetitions of the five-fold cross-validations (i.e. total 25 experiments) to enhance the robustness of the current preliminary study findings, future larger, multi-centre, and more diverse cohorts are still needed for further external validation. Secondly, the current study was conducted in a relatively controlled hospital setting, and although we instructed participants to walk at their usual pace, the possibility of potential Hawthorne effects (or white coat effects) that may have influenced the participants' recorded gait patterns could not be excluded. Therefore, the transferability of the current findings to real-world, community settings should be further investigated. Third, although we used the clinical variables from the well-recognized FRS general CVD prediction system, it should be noted

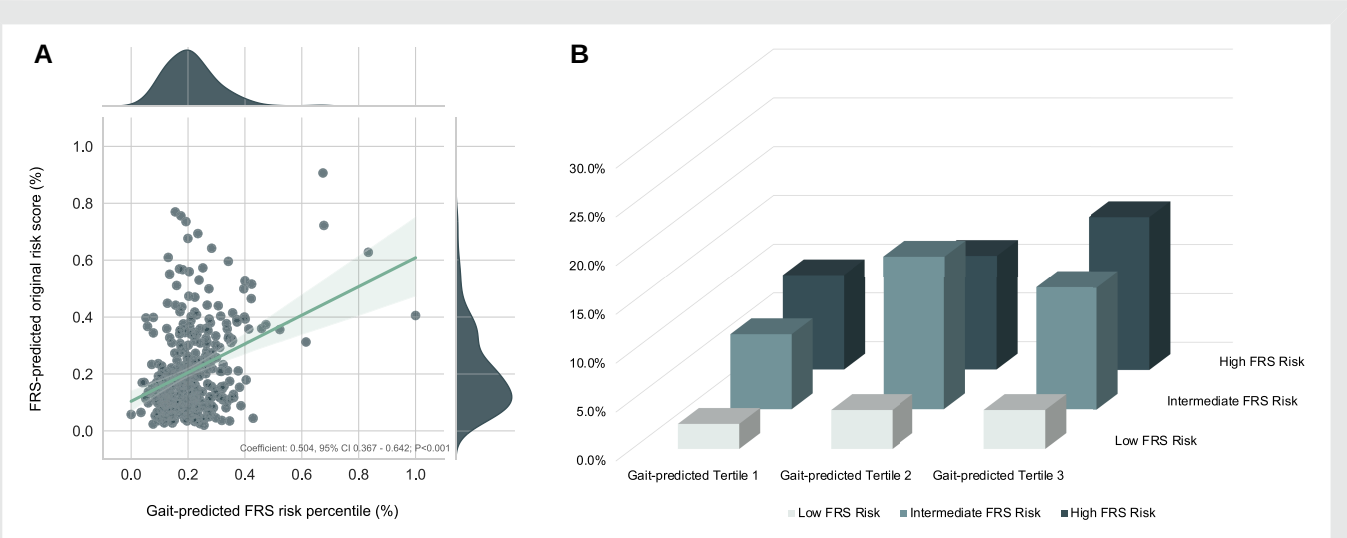


Figure 5 Relationship of gait information with the original FRS. (*A*) Correlation between the gait-predicted FRS percentile and the original FRS. (*B*) Two-factor risk subgroup stratification by both the gait-predicted CVD tertile and the original FRS category. FRS, Framingham Risk Score.

that the original FRS tool was not designed to predict the cross-sectional CVD prevalence but to assess future CVD risk. The current clinical model based on these clinical variables was simply intended to establish a baseline performance measure of conventional clinical information in assessing CVD. Thus, the current performance results of the clinical model do not reflect that of the original FRS tool. Additionally, the choice of the clinical variables from the FRS as a clinical baseline was primarily the result of a balance between the intended disease target and data availability in our current study. There are surely other more complex and effective metrics or examination approaches to represent the general predictive value of conventional clinical information for CVD assessment, depending on the accessibility or clinical setting. Fourth, it should be noted that the current study participants were individuals referred to the hospital for confirmatory CVD examinations. Consequently, they represented a more selective and higher-risk population. This may differ from one of the potential application scenarios of general CVD risk assessment in primary care settings. Future research should aim to validate the current proof-of-concept findings in the clinical setting with the intended target populations. Fifth, it should be mentioned that the specific product line of the Kinect camera used in the current study has been discontinued since 2017, which may lead to potential accessibility issue. However, there are currently many other available alternative camera devices with sensor technology that can achieve similar functionality and performance. Therefore, the current gait video-based approach should not be limited to one specific device, but we do need to test other devices in future studies for generalizability. Finally, the current video-based gait analysis approach employed in the present study had certain quality requirements for the gait videos, which resulted in a proportion of gait videos not able to be included in the final analysis. Future studies should explore new analysis methods that are more flexible and less stringent on gait video data and should also give more consideration to environmental factors, especially when implemented in real-world settings.

Conclusion

In present study, we demonstrated the association between the gait video information and the underlying general CVD status. The gait features extracted from gait video exhibited significantly better predictive value for the composite general CVD status as well as specific cardiovascular conditions like PAD and HF, when compared with tradition clinical variables. The current findings suggest the potential of a non-contact, video-based gait analysis approach as a new paradigm of continuous monitoring and dynamically updated CVD assessment. Future studies are warranted for further validation.

Supplementary material

Supplementary material is available at *European Heart Journal – Digital Health*.

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Conflict of interest: none declared.

Data availability

The data collected and analysed in the current study cannot be shared publicly due to patient privacy. All data were approved for research purposes in Fuwai Hospital only. Any external use requires additional consent and ethical approval from Fuwai Hospital institutional review board and may be available from the corresponding author on reasonable request.

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