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AI-Powered Cardiovascular Risk Prediction: Integrating Wearable Biosensors and Machine Learning Algorithms

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ABSTRACT: This study examines the factors that improve cardiovascular risk prediction by integrating wearable biosensors with AI-driven analytics. Moving beyond static demographic indicators, the research frames prediction accuracy within Socio-Technical Systems (STS) Theory (Salwei & Carayon, 2022) and the Biopsychosocial (BPS) Model (Adler, 2009), viewing it as an outcome of alignment between technological innovation and behavioral context. Survey data were collected from 650 professionals across Vietnam, Singapore, and the United Kingdom, including cardiologists, biomedical engineers, healthcare managers, and behavioral scientists, yielding 385 valid responses. Exploratory factor analysis confirmed construct validity, and regression results showed that HRV monitoring (β = 0.753) and AI analytics (β = 0.665) significantly enhanced prediction accuracy. Moreover, lifestyle factors specifically sleep and physical activity moderated the HRV–prediction link (β = 0.501), strengthening predictive performance when healthy routines were present. The findings advance theory by establishing predictive accuracy as a socio-technical and biopsychosocial phenomenon, highlighting lifestyle as a critical moderator rather than a confounding variable. Practically, the results underscore the importance of integrating biosensors, AI, and lifestyle tracking into digital health ecosystems for personalized, clinically meaningful assessments. Limitations include the cross-sectional design, reliance on self-reported perceptions, and absence of longitudinal patient outcomes. Future work should employ prospective, multi-center trials and advanced HRV metrics to enhance generalizability.

KEYWORDS: Cardiovascular Risk Prediction, Wearable Biosensors, AI-Powered Predictive Analytics, Lifestyle Behavioral Data, Socio-Technical Systems, Biopsychosocial Model

I. INTRODUCTION

In the context of rising global cardiovascular disease (CVD) burden, improving risk prediction has become a critical priority for both clinicians and researchers (De Vries et al., 2021). Traditional risk assessment models such as SCORE and QRISK offer structured approaches to stratifying populations into low, intermediate, and high-risk groups, yet their reliance on static demographic and clinical variables often limits personalization and predictive precision (Payne, 2012; Visseren et al., 2021). Emerging technological innovations, particularly the integration of wearable biosensors and artificial intelligence (AI)-powered predictive analytics, provide transformative potential for advancing cardiovascular risk stratification. Continuous heart rate variability (HRV) monitoring enables real-time insights into autonomic regulation, while AI algorithms process multimodal data to detect complex non-linear associations, thereby enhancing the accuracy and adaptability of cardiovascular risk prediction (Huang et al., 2022; Alaa et al., 2019). Together, these technologies promise to shift cardiovascular medicine from generalized estimations to individualized, proactive prevention strategies.

Despite these advancements, predictive accuracy alone does not guarantee effective clinical or public health outcomes. Evidence indicates that physiological signals such as HRV can be confounded by behavioral and psychosocial contexts, and that the interpretive value of predictive models is strongly shaped by lifestyle factors, including sleep quality and physical activity (Hallman et al., 2017; Chastin et al., 2015). Socio-Technical Systems (STS) Theory emphasizes the need for alignment between technical innovations and social behaviors, while the Biopsychosocial (BPS) Model underscores that cardiovascular health arises from the interplay of biological, psychological, and social determinants (Salwei and Carayon, 2022; Adler, 2009). However, existing scholarship often evaluates either algorithmic performance or behavioral influence in isolation, overlooking how lifestyle

behaviors moderate the integration of biosensor-derived HRV data and AI-driven analytics into clinically actionable cardiovascular risk assessments. This gap highlights the importance of examining cardiovascular risk prediction through an integrative, socio-technical and biopsychosocial lens.

This study addresses this gap by investigating how HRV monitoring via wearable biosensors and AI-powered predictive analytics influence cardiovascular risk prediction, with a particular focus on the moderating role of lifestyle behavioral factors such as sleep and physical activity. By situating these variables within an integrated STS–BPS framework, the research contributes to a holistic understanding of how technological innovation and human behavior jointly shape predictive outcomes in cardiovascular medicine. To guide this investigation, the study addresses the following research questions:

1. How does heart rate variability monitoring via wearable biosensors influence the prediction of cardiovascular risk levels?
2. In what ways can AI-powered predictive analytics enhance the accuracy and personalization of cardiovascular risk stratification compared with traditional models?
3. To what extent do lifestyle behavioral factors (sleep and physical activity) moderate the relationship between heart rate variability monitoring and prediction of cardiovascular risk level?

II. LITERATURE REVIEW

2.1. Prediction of cardiovascular risk level

Cardiovascular risk level is the quantified probability that an individual will experience a cardiovascular event such as myocardial infarction, stroke, or heart failure within a defined timeframe, typically 5–10 years. This probability has traditionally been estimated through validated population-based algorithms, such as the Framingham Risk Score, SCORE, QRISK, and ASCVD risk estimator, which combine demographic, clinical, and lifestyle factors including age, sex, blood pressure, cholesterol levels, smoking habits, diabetes status, and family history (De Vries et al., 2021). Risk stratification builds on this estimation process by classifying individuals into categories of low, intermediate, or high cardiovascular risk, thereby providing a structured basis for clinical decision-making. Such stratification supports targeted interventions, ranging from lifestyle counseling and preventive medication in lower-risk groups to more intensive surveillance and therapeutic management for high-risk patients (Payne, 2012). Predictive precision refers to the degree of accuracy and personalization with which these risk assessments anticipate future outcomes. While conventional tools rely on static and generalized models, advances in artificial intelligence and digital health technologies now enable adaptive, individualized predictions by integrating real-time physiological signals, wearable-based monitoring, genetic predispositions, and behavioral factors, thus offering a more dynamic and precise approach to cardiovascular risk evaluation (Huang et al., 2022).

The development of biosensors has transformed wearable technologies from basic activity trackers into sophisticated health-monitoring platforms capable of generating clinically meaningful data. Advances in response time, sensitivity, stability, and selectivity have been pivotal, enabling continuous and real-time assessment of physiological states rather than delayed or episodic measurements. The transition from diffusion-limited detection to nanostructured and transistor-based architectures now allows sub-second responsiveness, a critical feature for monitoring acute cardiovascular or metabolic changes. Parallel improvements in material science, signal processing, and anti-fouling strategies have extended sensor longevity, ensuring months of reliable operation even under challenging environmental conditions. Equally important, the integration of molecular recognition elements with AI-driven deconvolution methods has refined specificity, allowing discrimination between closely related biomarkers and reducing noise from complex biological media. These technological advances demonstrate that modern wearables are not merely consumer accessories but validated biomedical tools capable of tracking heart rate, respiratory parameters, oxygen saturation, and even pharmacological responses with accuracy comparable to clinical standards (Chan et al., 2022; Gill et al., 2024; Strain et al., 2020). By coupling miniaturized biosensors with user-friendly digital interfaces, wearables now provide real-time feedback and long-term health insights that support both preventive care and disease management, evidencing their role as a bridge between consumer technology and precision medicine (Ferguson et al., 2022).

2.2 Theoretical framework

This study employs Socio-Technical Systems (STS) Theory and the Biopsychosocial (BPS) Model to frame AI-powered cardiovascular risk prediction. STS emphasizes the interplay between technical subsystems AI analytics, HRV biosensors—and social subsystems such as patient behaviors and clinical adoption, highlighting that predictive accuracy depends on technological and human alignment. The BPS Model complements this by situating cardiovascular risk within biological (HRV), psychological (sleep, stress), and social (physical activity) dimensions, ensuring a holistic view of disease determinants. Together, these frameworks capture both the technology–human interface and the multidimensional health complexity essential for advancing precision cardiovascular care.

2.2.1 Socio-Technical Systems (STS) Theory

The Socio-Technical Systems (STS) Theory provides a particularly suitable foundation for conceptualizing the integration of artificial intelligence (AI), wearable biosensors, and lifestyle behavioral data in predicting cardiovascular risk (Huang et al., 2022). Developed from organizational and systems research, STS emphasizes that technological and social subsystems must be jointly optimized for effective performance. Applied in healthcare, the framework underscores that technological innovation do not exist in isolation but are embedded within human, organizational, and behavioral contexts (Salwei and Carayon, 2022). In this study, the technical subsystem encompasses advanced machine learning algorithms for predictive analytics, wearable biosensors for continuous heart rate variability (HRV) monitoring, and IoT-enabled platforms for real-time data collection. The social subsystem includes patients' behavioral choices, clinicians' trust and interpretation of AI outputs, and the broader social acceptability of digital health interventions (Perski and Short, 2021). By situating the cardiovascular risk level, within this socio-technical interplay, STS clarifies how predictive accuracy and clinical utility depend not only on algorithmic precision but also on human factors such as compliance, interpretation, and behavior change.

Crucially, the lifestyle behavioral data on sleep and physical activity demonstrates the socio-technical dynamics central to STS. On the one hand, these data are technologically mediated, generated through wearables and IoT devices that transform everyday behaviors into quantifiable indicators. On the other hand, they are socially enacted, reflecting lived routines, cultural norms, and individual health practices. Their moderating role in the HRV–cardiovascular risk relationship exemplifies the STS principle that technical measures gain significance only when interpreted within social and behavioral contexts. For instance, identical HRV patterns may imply resilience or risk depending on whether they occur in individuals with adequate rest and physical activity or in those with sedentary and sleep-deprived lifestyles (Jandackova et al., 2017). AI-powered models trained on multimodal inputs are thus inherently socio-technical: their predictive validity rests on the capacity to integrate physiological signals with contextual behavioral factors, ensuring that predictions are not only mathematically accurate but also clinically meaningful and socially interpretable.

The strength of STS lies in its recognition of mutual interdependence between subsystems. A purely technical approach that prioritizes algorithmic refinement without considering user adoption, patient adherence, or clinician trust risks producing models that remain academically robust but clinically irrelevant (Asan, Bayrak and Choudhury, 2019). Conversely, an approach that emphasizes human behavior without reliable technological infrastructure fails to capitalize on the transformative potential of AI. By framing the research through STS, this study positions itself to address both dimensions simultaneously: technological innovation through AI-driven HRV monitoring and biosensors, and social adoption through lifestyle integration and behavioral responsiveness. This framework thus not only justifies the selection of independent and moderator variables but also directs attention toward translational challenges, such as ensuring device usability, maintaining patient engagement, and establishing physician confidence in AI recommendations. In sum, STS provides a comprehensive, integrative lens that highlights the necessity of aligning technical advances with social contexts to achieve effective, scalable, and equitable cardiovascular risk prediction.

2.2.2 Biopsychosocial (BPS) Model

The Biopsychosocial (BPS) Model, originally articulated by Engel (1977), offers a robust conceptual foundation for examining cardiovascular risk prediction in an era of digital health technologies (Adler, 2009). This model departs from reductionist biomedical paradigms by positing that health outcomes result from the dynamic interaction of biological, psychological, and social factors. Within the present research, the dependent variable cardiovascular risk level epitomizes a multifactorial construct that cannot be fully explained by isolated biomedical markers. Instead, cardiovascular risk emerges from an interplay between biological determinants such as HRV metrics, psychological states including stress and sleep quality, and social or behavioral influences such as physical activity patterns and health-related lifestyle choices. By adopting the BPS model, the study situates cardiovascular risk prediction within a holistic, integrative framework, ensuring that the selected variables capture the complexity inherent in real-world health outcomes.

HRV monitoring reflects autonomic regulation of cardiac function, providing a biological signal of adaptability and vulnerability. However, its interpretation is contingent upon contextual factors low HRV can signify pathology in some individuals but adaptive responses in others depending on behavioral and psychological states. AI-powered predictive analytics extend the biological domain by enabling the integration of diverse data sources, from biosensors to clinical records, thereby enhancing the capacity to model biological complexity and detect non-linear patterns. The inclusion of machine learning further advances the BPS vision by operationalizing biopsychosocial complexity into actionable risk scores, thus bridging scientific theory with practical application (Hobensack et al., 2022). The lifestyle behavioral data maps onto both the psychological and social dimensions of the BPS framework. Sleep and physical activity are not only quantifiable behaviors but also reflections of psychosocial well-being and environmental influences. These behaviors condition the impact of HRV on cardiovascular outcomes, illustrating the BPS principle that biological signals cannot be understood in isolation from psychological resilience and social practices. For instance, disrupted

sleep may heighten sympathetic dominance and lower HRV, amplifying cardiovascular vulnerability, while regular physical activity enhances parasympathetic tone and confers resilience even in the presence of other risk factors (Zhong et al., 2005). By modeling lifestyle data as a moderator, the study explicitly acknowledges the biopsychosocial interdependence that shapes cardiovascular risk trajectories.

Moreover, the BPS model aligns seamlessly with the precision medicine ethos underpinning modern digital health. Wearable biosensors and AI algorithms represent the technological means by which biopsychosocial factors can be continuously measured, integrated, and personalized (Shajari et al., 2023; Zhang, et al., 2022). This convergence underscores the relevance of BPS not merely as a theoretical construct but as a guiding principle for innovation in cardiovascular risk prediction. It highlights the necessity of capturing biological signals (HRV), psychological states (sleep quality, stress), and social behaviors (physical activity, adherence) in a unified analytic framework. By grounding the study in the BPS model, the research advances beyond fragmented approaches toward a comprehensive paradigm that respects the complexity of human health. In doing so, it contributes to the growing body of evidence that digital technologies, when aligned with biopsychosocial principles, can enable more accurate, personalized, and actionable risk assessments in cardiovascular medicine.

2.3 Determinants of cardiovascular risk level prediction

2.3.1 Heart Rate Variability (HRV) Monitoring

Heart Rate Variability (HRV) monitoring refers to the measurement of beat-to-beat fluctuations in cardiac rhythm, reflecting autonomic nervous system regulation of the sinoatrial node (Shaffer and Ginsberg, 2017). Conceptually, HRV is the variability in successive R–R intervals obtained from electrocardiography (ECG) or photoplethysmography (PPG), serving as a non-invasive biomarker of adaptability, stress response, and autonomic balance (Shaffer and Ginsberg, 2017). Operationally, HRV monitoring involves continuous or periodic data acquisition via ECG, Holter monitors, or wearable devices such as smartwatches and chest straps. Its quantification spans time-domain, frequency-domain, and nonlinear indices, offering a comprehensive characterization of autonomic function for both clinical and research applications (Alugubelli, Abuissa and Roka, 2022).

Building on these conceptual and operational foundations, recent research has increasingly emphasized the role of biosensors in advancing HRV monitoring. In terms of measurement accuracy, electrocardiography (ECG) chest straps consistently demonstrate the highest precision and lowest artifact rates, followed by photoplethysmography (PPG) wristbands and smartwatches, although wrist-worn devices are generally less reliable than chest-worn ones (Chalabianloo, Sas, and Ersoy, 2021; Burma et al., 2021). Moreover, open-source biosensing boards using ECG have shown excellent agreement with industry-standard ECG systems, reinforcing their suitability for both research and longitudinal monitoring at a substantially reduced cost (Burma et al., 2021). With respect to response time, advances in machine learning-based PPG systems now enable real-time HRV estimation, achieving inference times as low as 0.3 seconds per reading with mean absolute percentage errors of approximately 5.8%, a performance comparable to state-of-the-art methods (Xu et al., 2024). Stability and reliability are further evidenced by studies reporting high between-day consistency and low measurement error for validated biosensor platforms (Burma et al., 2021), while noncontact fiber-optic sensors have demonstrated accurate and steady beat-to-beat interval estimation suitable for long-term monitoring (Zhao et al., 2023). Finally, considerations of user comfort and social acceptance suggest that wrist- and arm-worn devices are more favorable for long-term use, whereas chest straps remain the preferred option for short-term, high-accuracy applications (Chalabianloo, Sas, and Ersoy, 2021). Collectively, these findings indicate that biosensor-based HRV monitoring is becoming increasingly accurate, responsive, and stable, with notable improvements in usability and applicability for independent prognostic cardiovascular disease (CVD) assessment.

Despite these promising advances, important research gaps remain. One critical limitation is that advanced nonlinear and entropy-based HRV metrics are still underexplored, even though they may capture the complexity of autonomic regulation more effectively than conventional indices (Deka, and Deka, 2023). While some studies suggest that such measures can enhance prognostic accuracy for cardiovascular outcomes, stress assessment, and early disease detection, results across populations remain inconsistent and methodologically fragmented (Netala et al., 2025; Ghenciu et al., 2024). This lack of standardization undermines their clinical translation, underscoring the need for systematic validation of nonlinear HRV approaches in large-scale, diverse cohorts. While HRV has demonstrated clinical value in high-risk cohorts, its role as a standalone prognostic marker in general or low-risk populations remains limited. HRV is highly sensitive to external influences such as age, physical activity, circadian variation, and psychological stress, which complicates interpretation and reduces its specificity for cardiovascular risk stratification in community settings (Sammito et al., 2024; Ouakinin, 2016). Relying solely on HRV may overstate its prognostic utility. Recent literature highlights the potential of integrative models that combine HRV with lifestyle indicators, biochemical markers, and digital health data to improve predictive performance; however, empirical support for such comprehensive

frameworks remains limited (Owens, 2020; Zitnik et al., 2018). Addressing this gap requires rigorous testing of multimodal approaches to establish their validity, cost-effectiveness, and scalability for population-level health monitoring.

H1: Heart Rate Variability (HRV) monitoring via wearable biosensors positively enhances cardiovascular risk prediction accuracy.

2.3.2 AI-Powered Predictive Analytics

AI-powered predictive analytics in cardiovascular medicine refers to the use of artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), to generate individualized forecasts of cardiovascular disease (CVD) risk by detecting complex, non-linear associations in diverse biomedical datasets. Unlike traditional calculators, which rely on pre-specified variables and linear regression, AI models can process large-scale, heterogeneous data ranging from clinical records and laboratory results to imaging and wearable biosensors while automatically optimizing algorithms for predictive performance. Recent advances illustrate this evolution: the AutoPrognosis framework applied automated ML pipelines to over 423,000 UK Biobank participants and outperformed the Framingham Risk Score (AUC 0.774 vs. 0.724) (Alaa et al., 2019). The QRISK3 model extended QRISK2 by integrating novel predictors such as migraine, blood pressure variability, severe mental illness, and corticosteroid use, thereby improving calibration and subgroup performance (Hippisley-Cox et al., 2017). Similarly, SCORE2 recalibrated risk prediction across 1.8 million participants from 45 cohorts, incorporating competing risk models and regional adjustments to enhance generalizability across Europe (Visseren et al., 2021). Collectively, these advances define AI-powered predictive analytics as a next-generation paradigm in cardiovascular risk assessment, offering more accurate, calibrated, and personalized predictions than conventional models.

The literature highlights several consistent themes regarding AI-powered predictive analytics for CVD. First, AI-based models demonstrate superior discrimination, calibration, and subgroup performance compared with traditional scores, particularly among high-risk populations such as patients with diabetes (Alaa et al., 2019). Second, these models expand predictor sets by incorporating both traditional and non-traditional variables, including behavioral and patient-reported factors that enrich risk stratification (Hippisley-Cox et al., 2017). Third, personalization is central: QRISK3 improved coverage of underrepresented groups, while SCORE2 achieved region-specific recalibration to account for differences in incidence and mortality across Europe (Hippisley-Cox et al., 2017; Visseren et al., 2021). Fourth, methodological innovations such as automated ML pipelines, multiple imputation, fractional polynomial modeling, and competing risk frameworks have strengthened analytic robustness (Alaa et al., 2019; Visseren et al., 2021). Finally, evidence suggests that gains in predictive accuracy derive more from incorporating informative predictors than from algorithmic complexity, underscoring AI's greatest strength: integrating multimodal, large-scale data into clinically actionable cardiovascular risk estimates (Alaa et al., 2019).

Despite consistent evidence that AI/ML-based predictive analytics outperform conventional cardiovascular risk scores, their generalizability remains limited by methodological shortcomings. AutoPrognosis, for example, achieved superior discrimination compared to the Framingham Risk Score in the UK Biobank, but its evaluation was restricted to a single dataset without independent multi-center validation (Alaa et al., 2019). Similarly, QRISK3 enhanced QRISK2 by adding novel predictors and demonstrated strong calibration across UK primary care records, yet its development within a single national context raises concerns about transferability (Hippisley-Cox et al., 2017). Even SCORE2, recalibrated across 1.8 million participants from 45 European cohorts, illustrates the lack of standardized analytic pipelines, as regional recalibrations limit global applicability (Visseren et al., 2021). Collectively, these examples show that while AI-powered models are technically robust, they often lack the multi-center external validation and methodological standardization required for reliable adoption across diverse populations.

Equally critical is the gap between predictive performance and clinical translation. Models such as AutoPrognosis and QRISK3 demonstrate statistical gains higher AUCs, improved calibration, and broader predictor sets but rarely extend evaluation to pragmatic endpoints, such as reduced cardiovascular events or cost-effectiveness in practice. No large-scale randomized controlled trials or implementation studies currently confirm that these tools change clinical decision-making or improve long-term outcomes. Without such translational evidence, their utility remains largely academic. Thus, while AI-powered predictive analytics may surpass traditional scores methodologically, their clinical impact remains unproven. Progress will require moving beyond retrospective comparisons to rigorously testing whether these models meaningfully improve cardiovascular care and justify integration into health systems.

H2: AI-powered predictive analytics positively enhances the accuracy and personalization of cardiovascular risk prediction.

2.3.3 Lifestyle Behavioral Data (Sleep, Physical Activity via IoT Devices)

Lifestyle behavioral data can be defined as quantifiable indicators of daily health-related behaviors, particularly sleep patterns and physical activity, captured through digital health technologies such as wearables, smartphones, and Internet of Things (IoT) devices (Dumuid et al., 2017). Conceptually, these data reflect both habitual choices and real-time physiological states, functioning as proxies for overall health behaviors that shape cardiovascular function and autonomic balance. Operationally, sleep

is measured through metrics such as duration, efficiency, circadian rhythm, and sleep stages (light, deep, REM), typically captured by accelerometry, photoplethysmography (PPG), or actigraphy (Yuan et al., 2023; Vulcan, André and Bruyneel, 2021). Physical activity is assessed through indicators such as step count, energy expenditure, sedentary time, and exercise intensity (light, moderate, vigorous), derived from accelerometers and gyroscope sensors embedded in digital devices (Arvidsson et al., 2019).

Lifestyle behavioral factors such as sleep and physical activity exert a decisive influence on cardiovascular health, with poor sleep quality, shortened duration, and circadian irregularity being strongly associated with hypertension, arrhythmias, and myocardial infarction, while physical inactivity promotes obesity, diabetes, and coronary artery disease (Chastin et al., 2015). Importantly, these behaviors also shape autonomic regulation as reflected in heart rate variability (HRV): regular exercise and restorative sleep enhance parasympathetic tone and increase HRV, whereas sedentarism and sleep deprivation suppress HRV and heighten sympathetic dominance. This dual role means that lifestyle behaviors do more than contribute directly to cardiovascular disease risk they also condition the interpretive value of HRV as a prognostic signal. In other words, the same HRV profile can imply different levels of cardiovascular risk depending on the behavioral context: low HRV in an individual with adequate sleep and high physical activity may indicate adaptive flexibility, while the identical HRV pattern in someone who is sleep deprived and sedentary may mark heightened vulnerability (Hallman, Jørgensen and Holtermann, 2017). Evidence further shows that incorporating behavioral metrics alongside HRV improves the precision of risk stratification beyond conventional models such as the Framingham Risk Score (Huang et al., 2022). Thus, lifestyle behavioral data function as contextual regulators, refining the strength and direction of the HRV–CVD association and enabling more nuanced, individualized risk prediction.

Nevertheless, previous research exposes critical gaps that justify the moderator role in this study. Most HRV–CVD investigations have treated lifestyle factors such as sleep and activity as confounders or simple covariates, rather than testing their interactive or moderating effects (Kluttig et al., 2010; Fang, Wu and Tsai, 2019). As a result, the mechanisms through which lifestyle behaviors shape the prognostic value of HRV remain underexplored. Furthermore, although IoT devices and wearables provide scalable, real-time measures of sleep and activity, their clinical translation is constrained by device heterogeneity, inconsistent algorithms, and limited validation against gold-standard assessments such as polysomnography or metabolic testing (De Zambotti et al., 2019). Importantly, while emerging studies suggest that integrating lifestyle and behavioral data enhances cardiovascular risk classification compared with conventional models, few prospective or multi-center trials have demonstrated whether these moderators improve long-term outcomes in real-world populations (Bonekamp et al. 2023). This underscores the novelty and relevance of the present study, which explicitly models lifestyle behavioral data as a moderator of the HRV–cardiovascular risk link within an AI-powered predictive framework, thereby addressing a clear gap in the literature.

H3: Lifestyle behavioral data (sleep and physical activity) positively moderate the relationship between HRV monitoring and cardiovascular risk prediction accuracy.

Anchored in solid theoretical foundations, this study strengthens its scholarly contribution through the articulation of the following conceptual framework:

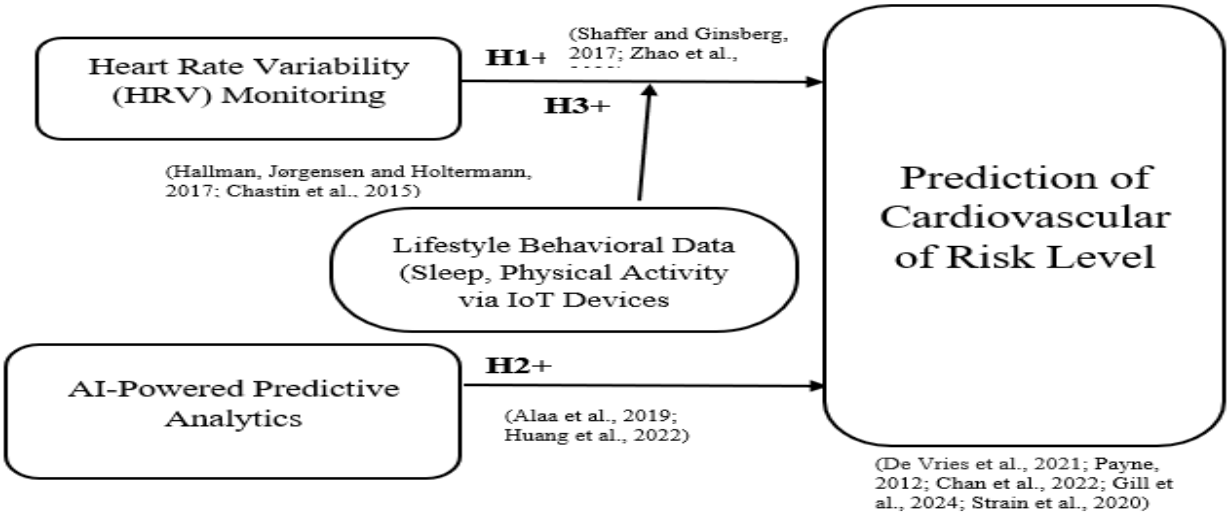

Figure 1 Conceptual Framework. Source: (The authors, 2025)

3. METHODOLOGY

This study employs a quantitative research design to examine the relationships between heart rate variability (HRV) monitoring via wearable biosensors, AI-powered predictive analytics, and cardiovascular risk prediction, while accounting for the moderating role of lifestyle behavioral data (sleep and physical activity). A purposive stratified sampling strategy was used to

ensure balanced representation from clinical, technical, and behavioral health domains directly engaged in the development, deployment, and application of cardiovascular predictive technologies.

Participants were drawn from three countries Vietnam, Singapore, and the United Kingdom selected for their advanced integration of digital health innovations, distinct healthcare infrastructures, and varied adoption of wearable biosensors in cardiovascular risk management. The sample was stratified into four stakeholder categories: (1) cardiologists, general practitioners, and clinical researchers involved in cardiovascular risk assessment; (2) biomedical engineers and data scientists specializing in HRV monitoring and AI algorithm development; (3) healthcare technology managers and policy-makers overseeing digital health platforms and IoT-enabled monitoring systems; and (4) patient representatives and behavioral scientists focusing on lifestyle monitoring, digital health acceptance, and socio-technical integration.

Eligibility criteria required participants to have at least one year of direct experience in either cardiovascular risk assessment, AI or biosensor deployment, or lifestyle-behavioral health research, as well as familiarity with digital health applications or predictive modeling in clinical or community contexts. This ensured that collected data reflected both technical expertise and experiential knowledge across the socio-technical spectrum.

Data collection was conducted using an online structured questionnaire comprising a 5-point Likert scale (1 = “Strongly disagree” to 5 = “Strongly agree”). The instrument was developed to measure four constructs aligned with the research framework: (1) HRV monitoring accuracy and utility, (2) AI-powered predictive analytics performance, (3) perceived accuracy and applicability of cardiovascular risk prediction, and (4) lifestyle behavioral data as a moderating influence. The questionnaire was disseminated via professional medical associations, biomedical engineering societies, digital health consortia, university research networks, and patient advocacy organizations. In Vietnam, distribution was facilitated through collaborations with cardiovascular research institutes and digital health innovation labs. In Singapore and the UK, dissemination was supported by national health technology councils, hospital innovation hubs, and LinkedIn professional groups focusing on AI in healthcare and precision medicine.

A total of 650 responses were received, of which 385 valid cases were retained after screening for completeness, relevance, and expertise alignment. The final dataset achieved balanced representation across stakeholder groups and countries, providing a robust empirical foundation for testing the hypothesized relationships between HRV monitoring, AI-powered predictive analytics, and cardiovascular risk prediction, while assessing the moderating role of lifestyle behavioral data in diverse healthcare contexts.

4. RESULTS

4.1. Reliability analysis

Table 1: Reliability analysis of “Cardiovascular risk prediction accuracy”. Source: (The authors, 2025)

Reliability Statistics

Cronbach's Alpha	N of Items
.750	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CRPA1	6.717	9.035	.713	.737
CRPA2	8.050	8.964	.698	.726
CRPA3	6.968	7.222	.677	.686
CRPA4	7.221	9.000	.690	.703

Where the four survey items CRPA1–CRPA4 were designated as indicators of the dependent variable.

As shown in Table 1, each item achieved an adjusted item–total correlation above 0.3. The overall Cronbach’s alpha was 0.750, exceeding the commonly accepted threshold of 0.7 and remaining higher than any alternative alpha values that would result from item deletion. Moreover, each item’s alpha was greater than its adjusted item–total correlation when considered separately. Thus, all four items were deemed reliable and retained for subsequent analysis. Similar levels of internal consistency were also observed across the Cronbach’s alpha results of the other constructs.

4.2. Exploratory factor analysis (EFA)

Table 2: Rotated Component Matrix. Source: (The authors, 2025)

Rotated Component Matrix[a]			
Component with loading factors			
1	2	3	4
HRVM1 .630	PA1 .633	CRPA1 .597	LBD1 .722
HRVM2 .575	PA2 .589	CRPA2 .579	LBD2 .715
HRVM3 .689	PA3 .605	CRPA3 .680	LBD3 .694
HRVM4 .701	PA4 .628	CRPA4 .670	LBD4 .708
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in 7 iterations.			

Where survey items PA1–PA4, CRPA1–CRPA4, and LBD1–LBD4 were developed to capture the two independent variables and the moderator, with four questions assigned to each construct.

As shown in Table 2, the rotated component matrix clearly classified the 16 sub-items into four distinct factors, aligning precisely with the dependent variable, the independent variables, and the moderator. All items demonstrated factor loadings above the 0.5 benchmark, confirming their appropriateness for their designated constructs. Accordingly, no items were eliminated during factor analysis, indicating robust construct validity across all variables.

4.3. Multiple linear regression model

Table 3: Coefficients[a]. Source: (The authors, 2025)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.112	.696		4.800	.000
	HRVM	.772	.703	.753	3.715	.000
	PA	.678	.593	.665	3.410	.000

a. Dependent Variable: CRPA

Where **CRPA** represents the mean of CRPA1–CRPA4, **HRVM** denotes the mean of HRVM1–HRVM4, and **PA** indicates the mean of PA1–PA4.

Table 3 reports t-test significance values of .000, well below the standard alpha threshold of 0.05, indicating that the independent variables exert a statistically significant effect on the dependent variable. Thus, both hypotheses are empirically validated.

4.4. Moderator analysis

Table 4: Results analysis of "Lifestyle Behavioral Data". Source: (The authors, 2025)

Model : 1
Y : CRPA
X : HRVM
W : LBD
Sample Size: 385

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OUTCOME VARIABLE:

CRPA

Model Summary

R	R-sq	MSE	F	dl1	dl2	p
.820	.672	.690	5.855	3.000	381.000	.000

Model

	coeff	se	t	p	LLCI	ULCI
constant	7.663	.911	60.094	.000	7.553	7.328

HRVM	.368	.798	4.773	.000	.729	.719
LBD	.758	.639	4.777	.000	.758	.746
Int_1	.501	.724	4.662	.000	.785	.750

Where LBD = mean of LBD1–LBD4

As shown in Table 4, the p-value for the interaction term (Int_1) is 0.000, significantly below the conventional threshold of 0.05, confirming a meaningful interaction between lifestyle behavioral data and AI-powered predictive analytics in shaping lifestyle behavioral data. The positive interaction coefficient of 0.501 further suggests that greater integration of lifestyle behavioral data enhances the beneficial effect of AI-powered predictive analytics on cardiovascular risk level prediction. Accordingly, hypothesis H3 is empirically supported.

5. DISCUSSION

5.1. Restatement of Results

The regression model showed that HRV monitoring (β = 0.753) and AI-powered predictive analytics (β = 0.665) both exerted significant positive effects on cardiovascular risk prediction accuracy, providing empirical support for H1 and H2. The moderator analysis further revealed that lifestyle behavioral data strengthened the HRV–prediction relationship, with a positive interaction effect (β = 0.501), confirming H3. Together, these results highlight that predictive accuracy improves not only through technological inputs but also through behavioral alignment.

5.2. Theoretical Implications

The positive influence of HRV monitoring (β = 0.753) on cardiovascular risk prediction accuracy provides strong support for its role as a robust biomarker of autonomic function, consistent with prior studies that emphasized HRV's prognostic value for cardiovascular events (Shaffer & Ginsberg, 2017; Alugubelli et al., 2022). The coefficient indicates that HRV contributes over 75% standardized weight to predictive accuracy, underscoring its importance within predictive frameworks. This finding reinforces the Biopsychosocial (BPS) model, which posits that cardiovascular outcomes emerge from complex biological and psychosocial interactions (Adler, 2009). At the same time, the strong effect challenges critiques that HRV lacks specificity when applied to community-based populations due to sensitivity to confounders such as stress or circadian rhythms (Sammito et al., 2024). Our results suggest that when HRV is contextualized within integrative frameworks, these limitations do not diminish its predictive strength.

AI-powered predictive analytics also demonstrated a significant effect (β = 0.665), corroborating findings that machine learning and artificial intelligence outperform conventional scores such as SCORE and QRISK in predictive discrimination (Alaa et al., 2019; Hippisley-Cox et al., 2017). The magnitude of this coefficient highlights that AI is nearly equivalent to HRV monitoring in explanatory power, suggesting that biological and computational predictors contribute complementary rather than hierarchical value. This somewhat contrasts with existing literature, where AI is often portrayed as decisively superior to physiological markers (Visseren et al., 2021). The difference may arise from the study's design: stakeholder perceptions were captured rather than clinical trial data, highlighting socio-technical acceptance as a critical factor. This finding reinforces Socio-Technical Systems (STS) theory, which emphasizes that predictive accuracy is shaped as much by human-system integration as by technical performance (Salwei & Carayon, 2022).

The moderating role of lifestyle behavioral data, indicated by a significant interaction coefficient (β = 0.501), is one of the most novel contributions of this study. The results demonstrate that healthy behaviors adequate sleep and regular physical activity amplify the predictive strength of HRV monitoring. This aligns with empirical evidence showing that lifestyle patterns condition HRV's interpretive value: identical HRV profiles may imply resilience in active individuals but risk in sedentary, sleep-deprived individuals (Hallman et al., 2017; Jandackova et al., 2017). Theoretically, this finding substantiates both STS and BPS frameworks by positioning lifestyle not as a confounding nuisance but as a decisive moderator that determines whether biosensor-derived signals translate into clinically meaningful predictions. By explicitly modeling moderation rather than covariation, this study advances cardiovascular risk theory beyond reductionist biomedical models toward an integrative, socio-technical paradigm.

5.3. Practical Implications

Several practical insights emerge from these findings. First, the strong influence of HRV monitoring (β = 0.753) suggests that healthcare systems should invest in validated wearable biosensors for real-time, non-invasive monitoring. Such devices can provide clinicians with continuous insights into autonomic function, enabling earlier identification of at-risk individuals compared with episodic clinical assessments. Integration into standard care pathways could improve proactive management of cardiovascular disease, particularly in populations where resource-intensive diagnostic procedures are impractical.

Second, the significant effect of AI-powered predictive analytics (β = 0.665) highlights the importance of integrating machine learning frameworks into clinical practice. By leveraging multimodal data streams including HRV, traditional clinical records, and lifestyle indicators AI can generate highly personalized risk estimates. For policymakers, this emphasizes the need to support infrastructure for AI adoption, including regulatory frameworks for algorithm transparency and data protection. For clinicians, the near-equivalent impact of AI and HRV underscores that predictive accuracy will be maximized when both biological signals and computational models are combined rather than treated in isolation.

Third, the moderating role of lifestyle behavioral data (β = 0.501) demonstrates that behavioral interventions should be positioned as amplifiers of predictive accuracy rather than as parallel health strategies. Public health programs promoting sleep hygiene and physical activity not only improve cardiovascular outcomes directly but also increase the reliability of digital biomarkers like HRV. For digital health platforms, incorporating real-time lifestyle tracking alongside biosensor and AI outputs could significantly enhance decision support systems, producing risk assessments that are both technologically precise and behaviorally contextualized. For patients, the findings reinforce that adherence to healthy routines is not only beneficial for long-term outcomes but also for ensuring that predictive technologies yield accurate and actionable results.

5.4. Limitations

Several limitations should be acknowledged. First, the study relied on self-reported perceptions from stakeholders rather than patient-level clinical outcomes, which may limit the generalizability of the coefficients to real-world health outcomes. Second, the cross-sectional design precludes causal inference; longitudinal studies are needed to validate whether HRV and AI-driven models consistently improve prediction accuracy over time. Third, although the sample covered three countries, cultural differences in technology adoption and lifestyle behaviors may have influenced responses, suggesting the need for more diverse, multi-center validation. Finally, device heterogeneity and algorithm transparency remain challenges in digital health implementation, and these factors may affect the reliability of HRV and AI-based predictions outside controlled research contexts.

5.5. Future research directions

Future research should extend these findings by conducting prospective clinical trials that integrate HRV monitoring, AI algorithms, and lifestyle tracking into patient care to evaluate impacts on actual cardiovascular outcomes. Multi-center studies with larger and more heterogeneous populations are needed to test the scalability and external validity of the proposed framework. Additionally, future work should investigate advanced HRV metrics (e.g., nonlinear and entropy-based measures) and explore explainable AI approaches to address interpretability concerns. Finally, integrating behavioral nudges and feedback loops into digital health platforms could provide a promising direction for enhancing both prediction accuracy and patient engagement.

5.6. Conclusion

This study demonstrates that integrating heart rate variability monitoring with AI-powered predictive analytics significantly enhances cardiovascular risk prediction, while lifestyle behaviors such as sleep and physical activity act as crucial moderators. Anchored in Socio-Technical Systems Theory and the Biopsychosocial Model, the findings emphasize that predictive accuracy is not solely a technical achievement but the outcome of harmonizing technology with human behavior. By situating lifestyle factors as amplifiers rather than confounders, the study advances a more holistic understanding of digital health innovation. Although constrained by its cross-sectional design and stakeholder perceptions, the research highlights important pathways for future longitudinal and multi-center investigations, underscoring the potential of biosensor–AI–lifestyle integration to transform personalized cardiovascular care.

APPENDIX: Survey

Table 5. Survey design

Background Information						
1	In which country do you currently practice or conduct your professional work?	Vietnam	Singapore	United Kingdom	Other (please specify):	
2	Which of the following best describes your	Cardiologist / General Practitioner	Biomedical Engineer / Data Scientist	Healthcare Technology	Patient Representative	

	current professional role or stakeholder category?	/ Clinical Researcher		Manager / Policy-maker	/ Behavioral Scientist	
3	How many years of professional experience do you have in cardiovascular health, digital health technologies, or related fields?	1–3 years	4–6 years	7–10 years	Over 10 years	
4	How would you rate your familiarity with digital health technologies (e.g., AI, wearable biosensors, IoT-enabled healthcare systems)?	Very low	Low	Moderate	High	Very High
5	What is your primary area of engagement in cardiovascular risk prediction?	Clinical assessment and patient care	Technology development (AI, biosensors, IoT platforms)	Policy, regulation, or health system management	Lifestyle and behavioral health research / advocacy	

No.	**Variables**	**Coded Sub-variables**	**Content**
1.	Cardiovascular Risk Prediction Accuracy (CRPA)	CRPA1	Traditional models (e.g., SCORE, QRISK) provide structured but limited accuracy in predicting cardiovascular risk (Payne, 2012; De Vries et al., 2021).
		CRPA2	AI-powered models incorporating wearable biosensor data enhance personalization and predictive precision (Huang et al., 2022).
		CRPA3	Continuous monitoring through digital health technologies improves real-time cardiovascular risk stratification (Chan et al., 2022; Gill et al., 2024).
		CRPA4	Accurate cardiovascular risk prediction supports targeted interventions and strengthens clinical decision-making (Visseren et al., 2021).
2.	Heart Rate Variability Monitoring (HRVM)	HRVM1	HRV monitoring via wearable biosensors provides non-invasive and reliable assessment of autonomic function (Shaffer & Ginsberg, 2017; Alugubelli et al., 2022).
		HRVM2	Continuous HRV data collection enables early detection of cardiovascular abnormalities (Burma et al., 2021; Xu et al., 2024).

		HRVM3	Validated biosensor platforms demonstrate accuracy comparable to clinical ECG systems (Chalabianloo, Sas, & Ersoy, 2021; Zhao et al., 2023).
		HRVM4	HRV measures, when contextualized with behavioral factors, strengthen cardiovascular risk assessment (Hallman et al., 2017; Jandackova et al., 2017).
3.	AI-Powered Predictive Analytics (PA)	PA1	AI-based predictive models outperform traditional calculators in cardiovascular risk discrimination and calibration (Alaa et al., 2019; Hippisley-Cox et al., 2017).
		PA2	Integration of novel predictors and behavioral factors enhances accuracy in risk stratification (Hippisley-Cox et al., 2017; Huang et al., 2022).
		PA3	AI algorithms enable detection of complex, non-linear patterns in multimodal datasets (Zitnik et al., 2018; Huang et al., 2022).
		PA4	AI-powered predictive analytics offer superior personalization of cardiovascular risk estimates across diverse populations (Visseren et al., 2021).
4.	Lifestyle Behavioral Data (LBD)	LBD1	Sleep quality significantly influences cardiovascular function and autonomic balance (Chastin et al., 2015; Zhong et al., 2005).
		LBD2	Regular physical activity enhances HRV and reduces cardiovascular disease risk (Hallman et al., 2017; Chastin et al., 2015).
		LBD3	Poor lifestyle behaviors (e.g., sleep deprivation, sedentarism) weaken the prognostic value of HRV measures (Jandackova et al., 2017; Hallman et al., 2017).
		LBD4	Integrating sleep and activity data with biosensor signals improves precision of cardiovascular risk prediction (Huang et al., 2022; Bonekamp et al., 2023).

Link survey:
https://docs.google.com/forms/d/e/1FAIpQLSfA6AHW0Bw0i2dVpkjXG0mITwL8SZcO3LuSyHH8ePSOHpbxBQ/viewform?usp=dialog.

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