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Individualized prediction of atrial fibrillation onset risk based on lifelogs

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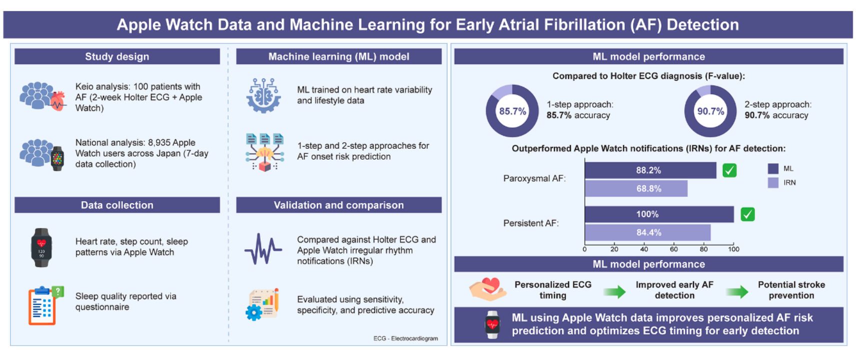
GRAPHICAL ABSTRACT



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ABSTRACT

Background and Objective: The Apple Watch alerts users to irregular heart rhythms and potential atrial fibrillation (AF), but delays in obtaining electrocardiograms (ECGs) after notifications can impede accurate disease diagnosis. We aimed to predict personalized AF risk using continuous Apple Watch lifelog data to facilitate timely ECG acquisition. We conducted two analyses: Keio and national. In the Keio analysis, AF patients underwent continuous 2-week Holter ECG monitoring, and a machine-learning model combining gradient-boosting decision trees and deep learning was developed. The national analysis recruited Apple Watch users across Japan to assess the model; data and survey responses were collected for seven days via a dedicated iPhone app.
Results: A total of 100 subjects (age: 63.9 ± 12.4 years, AF burden: 37.7 %) participated in the Keio analysis, while 8,935 subjects participated in the national analysis. Significant differences in Apple Watch data, including pulse rate ($p < 0.001$) and step count ($p < 0.001$), were observed between days with and without AF onset. Healthcare data measured by the Apple Watch, including sleep patterns, were significantly correlated with subjective survey responses ($p < 0.001$) and incorporated into the model. The model achieved an F-value of 90.7 % compared to diagnosis based on a 2-week Holter ECG. The model showed an additive benefit to Apple Watch irregular-rhythm notifications for AF detection (irregular-rhythm notification vs. model: 68.8 % vs. 88.2 % for paroxysmal AF and 84.4 % vs. 100.0 % for persistent AF).

Abbreviations: AF, atrial fibrillation; ECG, electrocardiogram; IRN, irregular-rhythm notification; TIA, transient ischemic attack; TTM, trans-telephonic monitor.

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Conclusions: Apple Watch-derived lifelogs enabled individualized AF onset risk assessment and the development of a machine-learning model for optimizing ECG timing for early AF detection.

1. Introduction

Pre-installed home-use medical applications of the Apple Watch notify users of atrial fibrillation (AF) signs as an irregular-rhythm notification (IRN) [1] and enable electrocardiogram (ECG) recordings [2]. Generally, cardiovascular disease tests with a longer recording time have higher detection sensitivity than those with lower recording times. Implantable devices have the highest sensitivity; however, due to their invasiveness, these devices cannot be used for mass screening. Portable ECG monitors offer a simple approach to recording ECGs; however, these monitors are not always carried by users. In contrast, the Apple Watch is worn consistently, although the collected data is not comparable to that of a medical test. Nonetheless, early disease detection through the utilization of the data collected by wearable devices is highly anticipated.

The Apple Heart Study in the United States highlighted the clinical value of the IRN, demonstrating its potential as a mass screening tool; [3] of the >400,000 subjects included in the study, 0.5 % received IRNs, and of these subjects, 34 % were diagnosed with AF using an adhesive ECG device that was mailed to them. However, the ideal number of subjects with AF could be higher, as the ECG was not recorded at the time of notifications. Since arrhythmias occur paroxysmally, Apple Watch users may miss AF onset due to the time lag between the notification and ECG testing. In addition, in the absence of symptoms, users may be unsure about when to record an ECG. However, understanding the likely timing of AF onset could improve early detection.

Therefore, this study aimed to establish the optimal timing for ECG recording by constructing a machine-learning model based on Apple Watch data collection.

2. Materials and methods

2.1. Study design

This study consisted of two analysis arms: Keio and national analyses, and the study protocol was approved by the Ethics Committee of the Keio University School of Medicine (Keio analysis, approval number 20200160, and national analysis, approval number 20200159).

2.2. Study population

(1) Keio analysis: 100 patients with AF who visited the Department of Cardiology at Keio University Hospital were included in the study for Keio analysis.
(2) National analysis: Apple Watch users in Japan who were able to wear an Apple Watch for 7 days while sleeping and answer a questionnaire were included in the study.

The subject selection criteria common to both analyses were as follows: age of ≥20 years; ability to download the study application from the App Store (Japan); Japanese citizenship and the ability to understand Japanese; and willingness to provide consent after receiving an explanation of the study content. Individuals unable to wear an Apple Watch while sleeping or operate the Apple Watch were excluded.

2.3. Endpoints

(1) Keio analysis: During a 2-week Holter ECG, ECG recordings were made via a portable ECG monitor (trans-telephonic monitor [TTM]). In addition, the subjects wore Apple Watches that collected healthcare data, including heartbeat and rhythm, using the electrical heart sensor. We then evaluated the characteristics of healthcare data based on the presence and absence of AF events, as well as testing modalities. Moreover, we constructed a model that notifies the optimal timing of pulse rate and ECG recordings for detecting arrhythmia.
(2) National analysis: A database was constructed from the healthcare data of Japanese citizens collected, which was then used to evaluate the model constructed during the Keio analysis.

2.4. Data acquisition

Data was acquired using an iPhone application designed for research purposes (Heart Study AW) (Fig. S1). The results of a 2-week Holter ECG and TTM, as well as medical record information, were obtained.

2.5. Observation

All subjects provided consent by clicking the consent button on the study application. Those in the Keio analysis also provided written consent. Subjects in the Keio analysis wore an Apple Watch and a 2-week Holter ECG while resting and sleeping, answered a questionnaire, and underwent regular cardiovascular medical examination, including TTM recording twice a day (morning and evening), as well as examination when they presented with symptoms. During the national analysis, one observation period involved wearing an Apple Watch while sleeping and answering a questionnaire the next morning, and the analysis included a total of seven observation periods.

2.6. Definitions

AF was defined as an irregular rhythm that lasted for at least 30 s on a 2-week Holter ECG, and each event was reviewed by two cardiovascular specialists. The sedentary period was defined as either the time identified as sleep in the data collected by the Apple Watch or a period in which three or more consecutive heart-rate readings all had an HKHeartRateMotionContext value of 1 (sedentary). A data interval of ≤360 s for the sleep and sedentary periods was considered "sleeping" and "sitting," respectively. Resting AF was defined as AF that occurred at rest. Persistent AF was defined as AF with a "resting AF duration/resting duration" ratio of >0.9 that lasted for at least 7 days.

2.7. Machine learning

Supervised machine learning was conducted using two approaches: 1-step and 2-step approaches (Fig. 1).

(1) In the 1-step approach, a model was constructed using a gradient-boosting decision tree, which has high predictive performance for tabular format data. One-hour time windows were set by dividing the period during which the subject wore a 2-week Holter ECG into hourly intervals, and we predicted whether resting AF would occur within the time windows. Features were created from the items of the collected data using an aggregation method that considers the characteristics of each dataset. Features that could be excluded without decreasing the accuracy of verification data were selected as explanatory variables. Hyper-parameters were selected by grid search.
(2) The 2-step approach consisted of the following two steps:

a. Step 2-a: We constructed a model that predicts whether AF would occur within 10 s after acquiring heart rate variability data from the Apple Watch. For this, we used deep learning with high predictive accuracy for time-series data.
b. Step 2-b: Using the three datasets of heart rate variability of the subject immediately before a time window, a predictive value was determined by the deep learning model constructed in Step 2-a. Instead of heart rate variability features, the predictive values were used with a gradient-boosting decision tree to construct a model that predicts whether resting AF would occur within a time window.

The results of the 2-week Holter ECG were used as training data, and data with a heart rate variability of up to 75 ms on the Apple watch were added as the data without AF. A model was constructed using data from 93 subjects in the Keio analysis and was further evaluated using the data from 66 subjects. In the national analysis, the 5977 subjects used for model training were also used as the population for model evaluation.

To evaluate the model, the onset risk of AF of each subject in a time window (the next 1 h) was estimated. A 5-fold cross-validation was performed to obtain predictive values for all subjects, and those exceeding the threshold were at risk of AF. In the 2-step approach, the predictive values of the deep learning model were obtained by performing an additional 2-fold cross-validation within each fold. The risk predicted by the model was compared with the presence and absence of AF on a 2-week Holter ECG, as well as the presence and absence of IRN on the Apple Watch.

2.8. Statistical analysis

Characteristics were analyzed using a chi-square test and paired *t*-test, and means, standard deviations, odds ratios, and 95 % confidence intervals (CIs) were calculated. A two-sided p-value $\leq$0.05 was considered statistically significant. To evaluate the CIs of the data, we performed 10,000 resamplings using the bootstrap method and derived two-sided 95 % CIs. All analyses were performed using SPSS Statistics version 28 (IBM Corp., Armonk, NY, USA).

3. Results

3.1. Subjects

The study analysis is depicted in Fig. 2. Of the 100 subjects from the Keio analysis, five with insufficient data due to poor compliance with the study protocol and two who requested withdrawal of consent and discontinuation of study participation were excluded; ultimately, 93 subjects were analyzed. The average age of the study population was 63.9 ± 12.4 (32–84) years. The Congestive heart failure, Hypertension, Age $\geq$75 years, Diabetes mellitus, prior Stroke or transient ischemic attack (TIA), or thromboembolism [doubled] ($CHADS_2$) score was 0.9 ± 1.0. The Congestive heart failure, Hypertension, Age $\geq$75 years [doubled], Diabetes mellitus, prior Stroke or TIA or thromboembolism [doubled], Vascular disease, Age 65−74 years, Sex category (CHA2DS2-VASc) score was 1.7 ± 1.5. Among the subjects, 69 (74.2 %) were male.

The total wearing time of the 2-week Holter ECG and the Apple

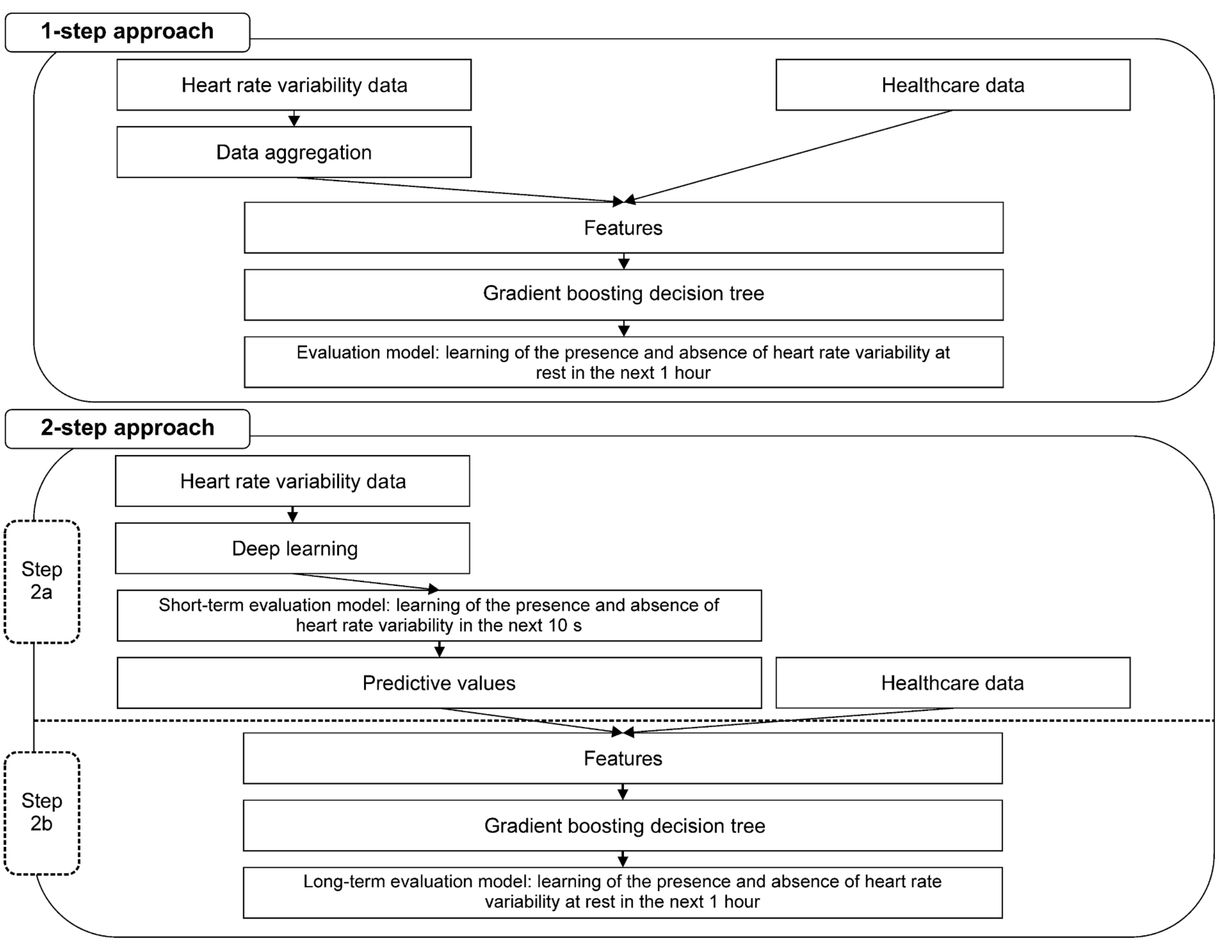

Fig. 1. Approaches for model construction
The 1-step approach, which uses a gradient-boosting decision tree, and the 2-step approach, which uses a gradient-boosting decision tree and deep learning, are performed to predict whether resting atrial fibrillation will occur within an hourly time window.

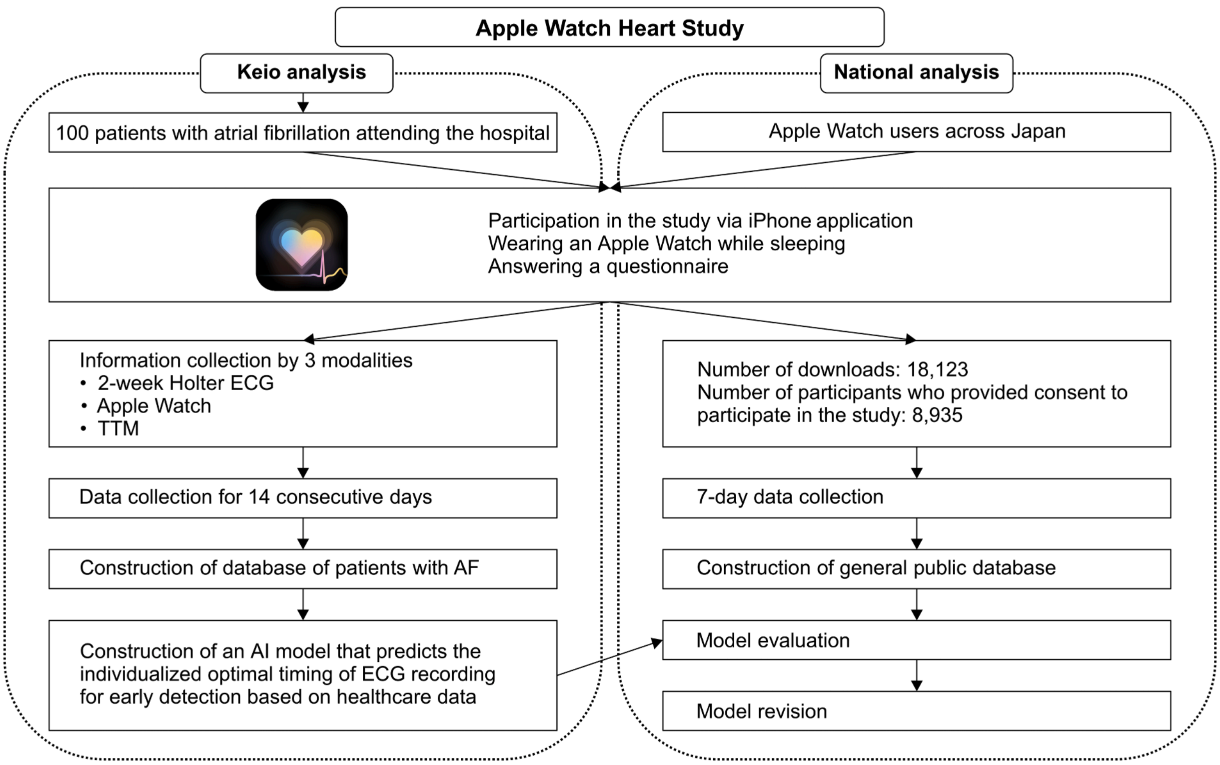

Fig. 2. Study flowchart
The study consists of the Keio analysis, which targets only patients with atrial fibrillation, and the national analysis, which targets Apple Watch users across Japan. Information is collected through an application designed for research purposes, and the machine-learning model constructed in the Keio analysis is evaluated in the national analysis.

Watch was 1297.9 and 1277.3 days, respectively. Sixty-nine subjects (74.2 %) had resting AF (resting AF occurrence: 1823 times) with an AF burden of 37.7 %. Twenty subjects (21.5 %) had persistent AF, and the AF burden was 21.4 ± 37.1 % for paroxysmal AF and 97.3 ± 10.1 % for persistent AF ($p < 0.001$). Forty-four subjects received an IRN; the recording time of resting AF was 38,241.5 ± 79,767 s ($n = 49$) in the group that did not receive an IRN and 169,653.5 ± 147,063.1 s ($n = 44$) in the group that received an IRN ($p < 0.001$); AF burden was 17.7 ± 36.3 % and 60.1 ± 44.9 %, respectively ($p < 0.001$). There was no difference in the wearing time of the Apple Watch ($p = 0.500$).

For the national analysis, 18,123 subjects downloaded the study application. Of the 8935 subjects who consented to the study, 7819 (87.5 %) transmitted data at least once, and 6408 subjects (71.7 %) completed the 7-day study. Subjects in the national analysis were younger than those in the Keio analysis (63.8 ± 12.4 years vs. 46.5 ± 13.3 years, $p < 0.01$), and there was no significant difference in sex ($p = 0.142$) between the analysis groups.

3.2. *Characteristic evaluation of testing modalities*

Among the subjects diagnosed with AF by the 2-week Holter ECG, diagnosis by TTM had positive and negative predictive rates of 90.4 % and 85.7 %, respectively (Table 1). The sensitivity for paroxysmal AF (93.4 %) was lower than that for persistent AF (100 %). The IRN by the Apple Watch had positive and negative predictive rates of 97.4 % and 57.1 %, respectively. The sensitivity for paroxysmal and persistent AFs was 68.8 % and 88.2 %, respectively. Both testing modalities had a specificity of 100 % and a positive predictive rate of 100 %.

3.3. *Characteristic evaluation of healthcare data*

The mean heart rate measured by the Apple Watch was 76.36 beats/min at AF onset and 61.05 beats/min during the non-onset period. The difference in the Apple Watch measured heart rate (15.30±5.37 beats/min) between AF onset and during the non-onset period was significant ($p < 0.001$). The daily step count before onset (7337.61 steps) was significantly higher than that before non-onset (5813.54 steps) (Δstep count: 1524.08±1289.66 steps, $p = 0.022$).

Table 1
Comparison of testing modalities.

Holter vs. Apple Watch		**IRN (+)**	**IRN (-)**
Holter AF (+)		37	12
	Paroxysmal AF	22	10
	Persistent AF	15	2
Holter AF (-)		1	16
Holter vs. TTM		**TTM AF (+)**	**TTM AF (-)**
Holter AF (+)		47	2
	Paroxysmal AF	30	2
	Persistent AF	17	0
Holter AF (-)		5	12
TTM vs. Apple Watch		**IRN (+)**	**IRN (-)**
TTM AF (+)		38	14
	Paroxysmal AF	23	12
	Persistent AF	15	2
TTM AF (-)		0	14

IRN: irregular rhythm notification, AF: atrial fibrillation, TTM: trans-telephonic monitor.

Comparing responses to the sleep questionnaire with the data collected by the Apple Watch, there was a significant difference in night awakening frequency ("I slept well" vs. "I slept normally" vs. "I could not sleep": 4.8 ± 3.4 times [$n = 294$] vs. 5.8 ± 3.8 times [$n = 415$] vs. 6.6 ± 4.8 times [$n = 111$], $p < 0.001$) and sleep duration ("I slept well" vs. "I slept normally" vs. "I could not sleep": 20,181.4 ± 8943.7 s [$n = 294$] vs. 19,731.1 ± 7961.1 s [$n = 415$] vs. 16,796.5 ± 7791.0 s [$n = 111$], $p =$

0.001).

3.4. Model construction and evaluation

Compared with diagnosis by the 2-week Holter ECG, prediction using the 1-step approach had sensitivity, specificity, positive predictive rate, and F-value of 79.6 % (two-sided 95 % CI: 67.9–90.2 %), 82.4 % (CI: 61.5–100.0 %), 92.9 % (CI: 84.0–100.0 %), and 85.7 % (CI: 76.9–92.7 %), respectively (Table 2). The 2-step approach had sensitivity, specificity, positive predictive rate, and F-value of 89.8 % (CI: 80.8 − 97.9 %), 76.5 % (CI: 53.8 − 94.4 %), 91.8 % (CI: 83.0 − 98.0 %), and 90.7 % (CI: 83.9 − 96.1 %), respectively, indicating improved model accuracy. The positive rates for IRN and the constructed model were 68.8 % (CI: 51.7 − 84.4 %) and 88.2 % (CI: 70.6 − 100 %), respectively, for paroxysmal AF, and 84.4 % (CI: 70.8 − 96.4 %) and 100.0 % (CI: 100.0 − 100.0 %), respectively, for persistent AF (Fig. 3).

In the national analysis model evaluation, 13.7 % (n = 817) of subjects were predicted to be AF-positive. The maximum value of heart rate variability was >50 ms in 813 subjects (99.5 %) and >100 ms in 633 subjects (77.5 %). The model distinguished between a pattern of heart rate variability with varying coupling intervals, which is characteristic of AF, and a pattern of heart rate variability with relatively constant coupling intervals, which is characteristic of extrasystole (Fig. S2).

4. Discussion

In this study, we constructed an artificial intelligence model that predicts the individualized risk of AF using the results of a 2-week Holter ECG of patients with AF as training data and utilizing healthcare data collected through the Apple Watch. The model showed an additive benefit to the irregular rhythm notification by the Apple Watch, demonstrating that its use may lead to early AF detection.

The Apple Watch continuously measures the pulse rate of the user while worn, and the application that notifies users of an irregular rhythm is a useful tool for the early detection of asymptomatic AF. With regard to accuracy, the Apple Watch has a higher positive detection rate than implantable cardiac monitors and cardiac implantable electrical devices [4,5]. However, the Apple Watch does not constantly monitor heart rate variability, and it is important to recognize that pulse wave technology and ECG R-R interval measurements are not equivalent, particularly with respect to factors, such as skin tone [6]. Therefore, its use in combination with another algorithm is warranted to further elevate its significance.

Previously, machine-learning models that predict future AF from ECGs of normal sinus rhythm [7–9] and a model that predicts the individualized onset rate of AF from existing datasets [10] have been evaluated. Stress, lack of sleep, and other factors are also known to be involved in the AF onset [11]. However, this degree of involvement varies depending on the subject; thus, the use of threshold values may not be accurate or feasible. By further developing these concepts, the present study pre-evaluated the changes in parameters previously reported to be associated with AF in each subject [12] and then included them as explanatory variables in the model. Then, we utilized home-life data collected through a wearable device as lifelogs and stratified the onset risk of each subject by predicting the occurrence of AF in a time window of the next 1 h. As a result, the model that we constructed identified the timing of the ECG recording that could detect new arrhythmias in 13.7 % of study subjects. Furthermore, we found that differences in subjective data, such as responses to a questionnaire, were reflected in differences in objective data automatically measured by the Apple Watch. This suggests that objective analyses of wearable device data may replace time-consuming subjective questionnaire surveys.

We recommend the use of Apple Watch ECG recordings when the model constructed predicts the onset of AF. This approach is significant both as a mass screening tool and for promoting the habit of ECG monitoring. A certain level of false-positive predictions from the model is anticipated. When the ECG indicates AF, users are encouraged to proactively share the findings with healthcare providers. Physicians can then confirm the diagnosis through hospital-based tests, such as 12-lead ECGs or Holter monitoring, facilitating early detection. This is because, in Japan, the Apple Watch ECG application is approved as a home-use medical device application; however, its classification results are not equivalent to a physician's diagnosis, limiting its role to a supplementary tool in medical practice. Therefore, social awareness initiatives are also required to connect alerts from wearable devices to early medical intervention.

AF itself is not a fatal arrhythmia, but its complication, stroke, can be life-threatening. Given the negative economic impact associated with stroke, early AF detection by a wearable device is considered economically cost-effective [13]. Moreover, the Atrial Fibrillation Network and the European Heart Rhythm Association stated that AF screening using artificial intelligence and new evidence-based approaches to rhythm management would improve outcomes for patients with AF [14]. Furthermore, this has been confirmed by real-world tracking studies [15]. However, all AF detected early should not be treated uniformly [16], and the need for treatment must be determined for each individual, taking into account personal background factors [17,18]. Establishing the common clinical significance of all healthcare data is difficult because data produced by different hardware have different characteristics [19]. However, the Apple Watch application now acts as a bridge to healthcare and medicine because it has emerged as a medical device application that analyzes data collected by a non-medical device and outputs the data to medical settings. As the use of wearable devices becomes more prevalent, further advancement in early diagnosis, effective treatment, and expansion of post-illness monitoring is expected.

This model was developed using a Japanese population and thus has limitations regarding its generalizability. The absence of healthy subject data in the Keio analysis and the lack of AF diagnostic data from Holter ECG in the national analysis are also limitations of this study. To validate its broader application within Japan, it is necessary to provide an application equipped with notifications based on this model. The external validity of the model should be evaluated by verifying whether the ECG recordings taken at the time of the notifications lead to early diagnosis in medical institutions. Challenges related to older adult individuals and socially vulnerable populations can be addressed by designing operational models that emphasize usability, such as interfaces designed for ease of use and systems that account for collaboration with caregivers. For global generalization, it is essential to consider the differences between Japan and other countries. Factors such as population composition, access to healthcare (including regular health checkups), lifestyle habits (e.g., salt intake, alcohol consumption, and smoking rates), and medical history (e.g., hypertension, diabetes, and obesity) are highly complex and interrelated. The prevalence of

Table 2
Model evaluation.

Keio analysis			
1-step approach		Model (+)	Model (-)
	Holter AF (+)	39	10
	Holter AF (-)	3	14
2-step approach		Model (+)	Model (-)
	Holter AF (+)	44	4
	Holter AF (-)	5	13
National analysis			
1-step approach		Model (+)	Model (-)
	IRN (+)	86	5
	IRN (-)	566	5319
2-step approach		Model (+)	Model (-)
	IRN (+)	91	0
	IRN (-)	817	5068

IRN: irregular rhythm notification, AF: atrial fibrillation.

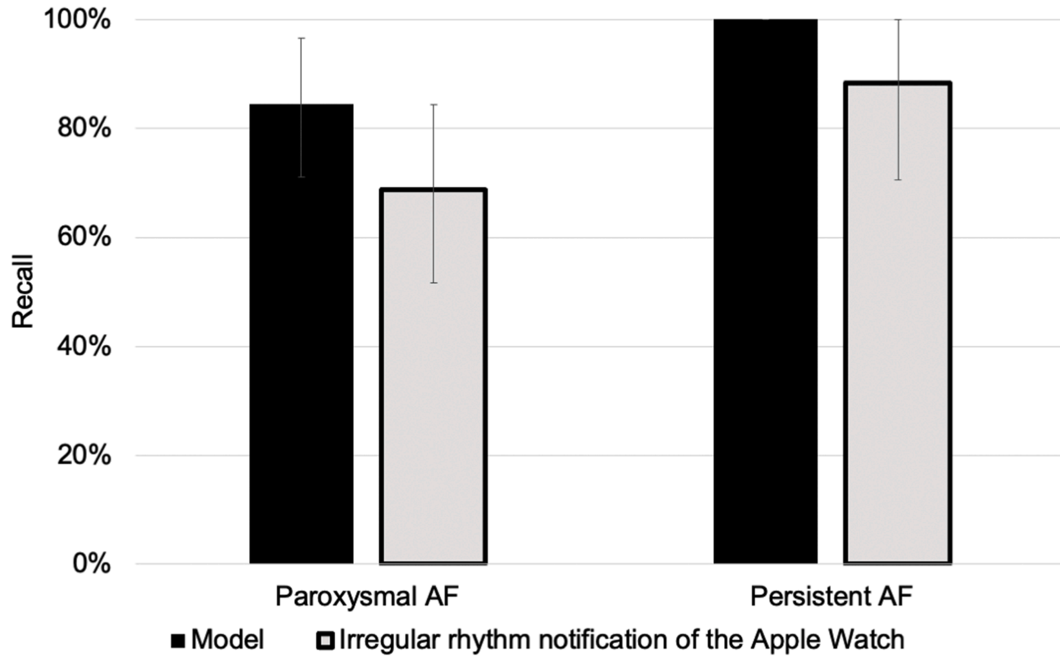

Fig. 3. Comparison of the irregular rhythm notification and the constructed model
The constructed model shows an additive benefit to the irregular rhythm notification in detecting the onset risk of atrial fibrillation, regardless of the type of atrial fibrillation.
AF: atrial fibrillation, Model: model constructed in this study, IRN: irregular rhythm notification.

diseases can vary significantly across countries and regions, influenced by the degree of aging, sex ratios, and other demographic characteristics. Additional contributing factors include social and genetic backgrounds, ethnic characteristics, and environmental influences. While it is impractical to comprehensively evaluate all these factors worldwide by comparing the model's predictions with AF detection using Holter ECG, the next steps should focus on validation in several countries. By leveraging Holter ECG, standard ECGs, or equivalent health data, research can progressively advance improvements in the model's generalizability through a phased approach.

In conclusion, we demonstrated that the use of lifelogs, collected through the Apple Watch, allows for individualized AF onset risk assessment using an artificial intelligence model that predicts the appropriate timing of ECG recording for early AF detection.

CRediT authorship contribution statement

Takehiro Kimura: Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis, Conceptualization. **Masahiro Jinzaki:** Supervision. **Hiroshi Miyama:** Data curation. **Kenji Hashimoto:** Data curation. **Terumasa Yamashita:** Data curation. **Yoshinori Katsumata:** Validation, Data curation. **Seiji Takatsuki:** Project administration. **Keiichi Fukuda:** Funding acquisition. **Masaki Ieda:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Role of the funding source

The study sponsors played no role in the study design; in the collection, analysis, and interpretation of data; in the writing of the report; and in the decision to submit the paper for publication.

Data availability statement

The data that support the findings of this study are available upon request from the corresponding author, TK. The data are not publicly available because they contain information that could compromise the privacy of research participants.

Consent

Participants were given either an application or written consent. All participants provided appropriate consent by clicking the consent button on the study application. Those in the Keio analysis also provided written consent.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ajpc.2025.100951.

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