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Artificial intelligence enabled mobile health technologies in arrhythmias-an opinion article on recent findings

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Introduction

Integration of ion channels and transporters and inherent property of automaticity of myocardial cells are necessary for the transmission of electrical impulses throughout the myocardium and the generation of a normal cardiac rhythm. When either of these, normal electrophysiological process of impulse generation or normal conduction of action potential gets disrupted, patients experience cardiac arrhythmias. The risk of acquired arrhythmias is significantly increased in presence of structural heart diseases, myocardial infarction and metabolic disorders. The majority of cardiac arrhythmias are categorised according to the rate at which they generate impulses or by where they originate in the myocardium. These include atrial fibrillation (AF), atrial flutter, ventricular tachycardia (VT), supraventricular tachycardia (SVT), ventricular fibrillation and bradyarrhythmias (1). With its rapid and erratic electrical signals in the atria, AF is the most prevalent type and causes ineffective contractions. AF patients present with shortness of breath, exhaustion, palpitations, and a higher risk of stroke. Anticoagulation therapy to prevent thromboembolic events along with antiarrhythmic medications, are common management strategies. Sudden cardiac arrest caused by ventricular arrhythmias results in patients losing consciousness. In these situations, immediate cardiopulmonary resuscitation (CPR) and defibrillation are critical for survival (2). Global estimates indicate that cardiac arrhythmias impact nearly 2% of the world's population and are linked to significant socioeconomic burden. According to recent research, machine learning algorithms may enhance the risk stratification for long-term cardiac arrhythmia. The development of mobile health technologies has provided customer-focused health care opportunities (3). In this opinion, the potential applications of the current and upcoming mHealth technologies for treating cardiac arrhythmias are illustrated.

Role of digital technologies in arrhythmia care

Contemporary portable gadgets designed for health monitoring, such as photoplethysmography and ECG systems (4) are not only affordable but the high-speed internet access of these sensors have enabled patients to access healthcare more widely. These technologies enable real-time monitoring and early arrhythmia detection, allowing patients to better manage their conditions and receive timely medical intervention (5). Using longer-term event recorders, 24–48 Holter, or medically certified ambulant

electrocardiogram (ECG) monitors has been necessary for the crucial step of correlating symptoms with rhythm. Long-term rhythm monitoring is made possible by mHealth devices, especially smartphone-based ECG and PPG technology, which is reasonably priced (6). Cardiac electrophysiology has been profoundly modified by AI and machine learning, with advancements in mobile technology enabling the measurement of heart-related physiological data. The healthcare industry now has access to a wealth of data, including accelerometers, ECGs, and PPG signals (7).

Atrial fibrillation screening

New developments in current contact-free plethysmography using smartphone cameras on the face and fingers have demonstrated promise for examining atrial fibrillation. AI algorithms demonstrate a high degree of cardiac rhythm discrimination when used for ECG readings, including those recorded with mobile cardiac telemetry. It will take thorough algorithm validation, data integration with the healthcare system, improvement of current clinical workflows, and strong patient access to turn these fascinating findings that lead to better clinical results expanded to unprecedented levels. Some excellent examples of recent innovations include the TeleCheck-AF

project, smartphone ECG surveillance, and home antiarrhythmic medication loading with smartphone tracings (8).

Smartwatches can detect irregular pulses, confirming AF diagnosis through ECG patch monitoring, as demonstrated in studies like Apple Heart Study (9) and Fitbit and Huawei Heart Studies (10). The HEARTLINE trial explores the impact of accessible devices like Apple Watch on early AF detection and clinical outcomes, while the LOOP trial explores anticoagulant use (11, 12). Population-wide AF screening may benefit, but its usability and detection depend on the screening modality and population characteristics. Diagnosis of AF is typically made through ECG or continuous ECG recording, but concerns about false-positive diagnoses arise from sensitivity and specificity variations. The detection rates of new AF have only ranged from 0.9%–7.4% using handheld ECG monitors like Merlin, which rely on automated algorithms and have sensitivities ranging from 93%–100% (13). PPG and ECG-based wearables can identify AF in patients with previous AF, anti-arrhythmic medications, cardioversion, or ablation as highlighted in Table 1. While ECG is still the gold standard for diagnosing AF, PPG is already found in the majority of commercially available smartphones and wearable technology, making it a low-cost way to monitor arrhythmias even if it doesn't allow for precise diagnosis. Further ECG evaluation is necessary to confirm arrhythmias identified by PPG alone.

TABLE 1 Validated devices involving mHealth technologies for arrhythmia.

Type of Device	Study	Sensitivity (%)	Specificity (%)	Arrhythmia	Pros	Cons
Hand-held ECG devices	Zenikor (14)	96	92	AF	Cloud-based analysis service	No display of ECG tracings
	MyDiagnostick (15)	100	96	AF	Recording and storage device	Rechargeable battery not available
	Merlin ECG event recorders (13)	93.9	90.1	AF	Display of ECG recordings	Rechargeable battery not available
Wearable PPG based	Apple Watch (9)	98	90.2	AF/flutter/SVT	Simple technology. Easy to carry. FDA approved	Blood pressure cannot be measured. PPG sensor consumes more power. Expensive.
	Fitbit (10)	68	98	AF/flutter/SVT	Easy to carry. FDA approved	Blood pressure cannot be measured. Expensive.
Smartphone ECG based	AliveCor Kardia (16)	98	97	AF/flutter	ECG recordings displayed	iphone/android is required
	AliveCor (17)	Alivecor is accurate in measuring QTc interval ($P < .01$)		QTc in sinus rhythm Easy to carry	ECG recordings displayed	iphone/android is required
	AliveCor Kardia (18)	89	91	SVT	ECG recordings displayed Easy to carry FDA approved	iphone/android is required
Pulse wave analysis	Pulse-smart (36)	97	93.5	AF, PVC	Can distinguish between sinus rhythm and irregular abnormal pulse. Easy to use.	Noise and light affect accuracy.
Smartphone PPG based	Cardio Rhythm (19)	92.9	97.7	AF/flutter	Low cost. Automatic beat to beat measurement of HR.	Android application needed
Wearable ECG based	Necklace-ECG (20)	99.1	98.5	AF	ECG tracings available. Easy, simple.	Continuous wearing is required.
	Samsung Simband 2.0 (21)	98.2	98.1	AF/flutter	Both ECG and PPG recordings are obtained.	Android is necessary
Holter based-continuous monitoring	Zio Patch (22)	96 arrhythmia events detected		AF, SVT, VT	No battery charging required FDA approved	Prolonged wearing

ECG, electrocardiography; PPG, photoplethysmography; AF, atrial fibrillation; PVC, premature ventricular contraction; SVT, supraventricular tachycardia; VT, ventricular tachycardia; QTc, corrected QT interval; HR, heart rate.

Atrial fibrillation management and the potential risk of stroke

The potential of PPG and ECG-based wearables to identify AF in patients with a history of AF, anti-arrhythmic medication use, cardioversion, and ablation has been confirmed by certain studies using artificial neural network (23). Integrating mobile technologies with a “pill in the pocket” approach could provide benefits like closer monitoring, early antiarrhythmic medication administration, confirmatory validation of symptoms, and avoiding side effects and emergency medical visits (24).

In order to predict paroxysmal AF on ECGs from patients in sinus rhythm, the Mayo Clinic created the first AI-ECG algorithm using almost 650,000 ECGs. Furthermore, the use of AI-ECG for AF estimation was investigated in patients who had an embolic stroke of unknown cause, in which silent underlying AF is often suspected to be the cause (25). AI/ML techniques may also present the chance to stratify patients based on outcomes, like the likelihood of a stroke or the success of cardioversion, in the context of a new AF diagnosis. The ML models outperformed the CHA2DS2-VASc and HATCH scores in predicting the risk for ischemic stroke, but they were less effective than the scores in predicting 6-month AF recurrence, 6-month rhythm control, and pharmacological cardioversion success (26, 27). Regardless of the AF pattern (silent or paroxysmal) or whether the AF burden is low due to automatic cessation of rhythm control techniques, current guidelines advise lifelong anticoagulation based on risk factors.

Role of mHealth in ventricular and supraventricular arrhythmias

SVT is challenging to diagnose due to its unpredictable nature and lack of diagnostic yields. Traditional methods have diagnostic yields ranging from 10% to 50%–60%. mHealth devices offer long-term, affordable rhythm monitoring, effectively diagnosing patients experiencing brief episodes of prolonged palpitations. Smartphone-based single-lead ECGs have a high resolution to distinguish SVT from sinus tachycardia misdiagnosis (89% sensitivity and 91% specificity). However, only 51% of surveyed doctors would proceed with an invasive EP study based on symptomatic, regular tachycardia (18). mHealth devices may mistakenly diagnose palpitations caused by PVCs as AF due to irregular rhythms. Discrimination algorithms could address this issue. Smartphone-based algorithms have successfully distinguished PVCs from sinus rhythm, PACs, and AF with 96% accuracy. A computational algorithm created a feature matrix from QRS attributes from a smartphone-connected ECG device, showing 98.69% PVC recognition accuracy. Smartphones may be helpful in diagnosing ventricular arrhythmias, as evidenced by case reports (28, 29). According to the 2019 guidelines published by the European Society of Cardiology (ESC), mobile recording devices may be required for the diagnosis of supraventricular tachycardias (SVT) due to their ease of use, but validation is necessary. EP-guided ablation, a potential treatment, can be

accelerated with the use of smartphone-based one-lead ECG recordings. Unfortunately, quantifying burden is difficult due to the irregular nature of SVTs (30).

Use of mHealth application for arrhythmia care in children

Paediatric and congenital heart populations are quickly adopting mHealth technologies, despite the fact that these tools were created and validated in the adult population. When compared to traditional 12-lead ECGs in children, a few mHealth devices, like the Apple Watch and Alive Cor Kardia Monitor (31), have been evaluated for symptom-rhythm correlation and QT evaluation with high quality data (32). ICDs are effective in saving lives for patients with high risk of sudden cardiac death (SCD), but they don't significantly reduce sudden deaths. Machine learning can develop algorithms to recognize reduced left ventricular function from a 12-lead ECG, which predicts ICD benefit (33). Traditional markers and AI-based markers struggle to improve mortality rates by predicting positive and negative values and identifying modifiable physiological processes. Wearable technology measuring heart rate variability (HRV) can improve general health, but its efficacy is limited due to limited data in controlled settings (34).

Limitations of mHealth technologies

For various stakeholders, integrating digital health technologies into the treatment of patients with arrhythmias poses a number of challenges. Healthcare providers encounter challenges like a lack of knowledge about the features of the devices, a lack of confidence in their use, and worries about liability. Challenges for patients and consumers include the need for additional testing, socioeconomic disparities that impact access, potential anxiety related to test results, and differing levels of digital literacy. Operational difficulties include continuous charging of devices, cybersecurity threats, data storage problems, insufficient investment in workflows to handle the growing number of devices, and the incorporation of device data into electronic health records. Additionally, the adoption of these technologies in the healthcare landscape is made more difficult by the absence of clear guidance on legal obligations and reimbursement proceedings (35).

Conclusion

High cardiac rhythm discrimination is demonstrated by various AI algorithms in ECG readings. According to recent research, AI algorithms may enhance the risk stratification for long-term ventricular arrhythmia. However, for widespread clinical results, additional validation, data integration, clinical workflow enhancements, and patient access are required. Data from wearable devices being incorporated into electronic medical records (EMRs) is crucial for efficient clinical review and decision-making. However, clinician time is a significant barrier to this integration.

By reducing the need for frequent office visits and intervention, these systems can ensure consistent and effective patient care. Clinical data is essential for confirming device accuracy and determining the effectiveness of interventions based on findings. Progressive automation may be an option, but systems should begin as semi-automated. However, to evaluate the clinical usefulness of machine learning models in enhancing subsequent ventricular rhythm disturbances, additional investigations with bigger sample sizes, robust validity, more varied patient samples, are required.

Author contributions

AB: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

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