ECG data accuracy captured with at-home devices by qualified healthcare professionals compared to patients

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Abstract

Cardiovascular Diseases (CVDs) are a leading cause of death worldwide. General at-home care has been shown to improve patient outcomes, decrease hospital admissions, and prevent fatal arrhythmias. The purpose of this research is to frame the use of at-home electrocardiograms (ECG) and the ECG readability across two groups: conducted by qualified healthcare professionals at a clinic and conducted by patients or their caregivers at-home. The results compare at-home ECG readability measured by patients and their caregivers with the control group, represented by ECG readability taken by qualified healthcare professionals during routine office visits. This research study also evaluated data for the accuracy level in ECG data using a 12-lead internal and three external leads. With the growth of modern healthcare technology, it is now possible for patients to be more proactive in monitoring their CVD by conducting at-home ECGs with real-time feedback from their cardiologist to identify any abnormalities. At-home medical-grade ECGs can lead to early identification of heart arrhythmia and decreased hospitalization frequencies. Results from this study support the need for effective coaching and training of patients and their caregivers in using at-home ECG.

Keywords: Knowledge sharing, at-home medical device, the accuracy of at-home ECG device, improved patient care with a wearable device.

Introduction

Cardiovascular Diseases (CVDs) are a leading cause of death worldwide. According to the World Health Organization (WHO) (2023), CVDs account for 17.9 million deaths per year. General athome care has been proven to improve patient outcomes and decrease hospitalization readmission (Howard et al., 2019). Athome hospitals in this study are defined as a care model that brings hospital-level care, including the use of hospital-level medical-grade devices with clinical accuracy, directly to a patient's home (Leff, 2009). With the growth of modern healthcare

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technology, advances in sensor innovation, communication, and data processing as well as detection of device malfunction, it is now possible for patients and their treating medical doctors to be more proactive in monitoring their CVD. At-home electrocardiogram (ECG) monitoring can be utilized with real-time feedback from the cardiologist to identify any abnormalities (Steinhubl et al., 2018; Serhani et al., 2020). This study defines at-home ECG monitoring as a type of technology that allows patients to take ECG readings from the comfort of their homes. ECG readability can be defined as how easily identifiable the different parts of an ECG are, with a high degree of readability displaying clear P-waves, Q waves, R waves, S waves (also known as "QRS complexes"), and T-waves, leading to an informed diagnosis. At-home medical-grade ECGs can lead to early identification of heart arrhythmia and decreased hospitalization frequencies, resulting in lower costs, and decreased stress, all of which increase the overall quality of life for the patient and their caregiver (Marston et al., 2019). Thus, the main goal of this research is to compare data on ECG readability from patients and their caregivers, who conducted at-home ECGs in the experimental group, versus data on ECG readability from patients at routine office visits, where a qualified healthcare professional takes the ECG readings as the control group. Another goal of this study is to evaluate the accuracy level in ECG data across each patient from the initial point of ECG measurement to the final point. This study aimed to address three key hypotheses (in null form):

- H1: There is no statistically significant mean difference between the accuracy level of ECG data taken by patients, or their caregivers, compared to those taken by qualified healthcare professionals.
- H2: There is no statistically significant mean difference on each of the ECG 12-leads accuracy levels between data taken by patients or their caregivers compared to those taken by qualified healthcare professionals.
- H3: There is no statistically significant mean difference on average for the ECG 12-leads accuracy level as the patient diagnoses are more complex (i.e., the patient's number of diagnoses of complex chronic diseases increases from 2 to 8).

Background

History of Electrocardiogram (ECG) Devices

An electrocardiogram (ECG) is considered one of the most useful diagnostic tools in medicine for cardiac conditions (Jevon, 2010). It is a non-invasive device that is used to evaluate the activity of the heart with electrodes, wired leads, and an ECG device that records the activity to be used for interpretation (Dupre et al., 2005). Electrodes are attached to specific areas on the patient's body, typically on the chest and arms. The electrodes are connected to the ECG device by leads through which the electrical activity of the heart is measured. The overall ECG is a measure of the electrical impulses of the heart, both the atrial and ventricles, and can be used to evaluate heart rate, heart rhythm, and potential cardiac abnormalities (Jevon, 2010). The first look into measuring the electrical activity of the heart began with Dr. Luigi Galvani in 1786 when he discovered that electrical impulses from skeletal muscle were capable of being captured (AlGhatrif & Lindsay, 2012). In 1891, Bayliss and Edward Starling used a capillary electrometer to measure the electrical

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activity of the heart and discovered the triphasic nature of the heart (AlGhatrif & Lindsay, 2012). Years later in 1901, Dr. Willem Einthoven coined the three-lead string galvanometer electrocardiograph (AlGhatrif & Lindsay, 2012). In 1909, the first ECG machine was introduced to the United States at Mt. Sinai Hospital, New York (AlGhatrif & Lindsay, 2012). While the three-lead ECG was adequate for assessing cardiac arrhythmias, it was quickly discovered that the three leads were not enough for detecting problems such as myocardial infarction (AlGhatrif & Lindsay, 2012). In 1942, Dr. Emanuel Goldberger added additional unipolar leads to the left and right arms, leading to increased coverage of the heart with 30-degree increments, as opposed to the 60-degree increments seen in the three-lead ECG (AlGhatrif & Lindsay, 2012). The incorporation of the unipolar leads concluded the major advancement toward the 12-lead ECG, which is widely used in hospital systems today and is the recommended ECG for use by the American Heart Association (AlGhatrif & Lindsay, 2012). The 12-lead ECG is the gold standard for the evaluation of cardiac complaints today. It can accurately display the QRS, ST, and T intervals of the heart, which can be used to diagnose numerous cardiac abnormalities (Nam et al., 2014). With the rapidly growing field of technology and its intersection with medicine, at-home 12-lead ECGs are now available not only for diagnosing cardiac issues but also for monitoring patients with chronic cardiac conditions. At-home medical-grade 12-lead ECGs have been shown to lead to earlier recognition of cardiac abnormalities and are associated with reductions in shortterm mortality due to cardiac complications (Nam et al., 2014). This highlights the benefit of athome ECGs and reinforces the importance of continuing to improve the accuracy and readability of ECGs performed at-home.

Accuracy of Medical Devices

The utilization of medical devices in the healthcare system often depends on their accuracy, defined as "the closeness of agreement between a measured quantity value and a true quantity value of the measurement" (Squara et al., 2015, p. 67). Medical devices, including ECG devices, must display a high degree of accuracy to lead to the best patient outcomes. Oftentimes, healthcare providers create treatment plans and make diagnoses for patients partly based on results from medical devices. Therefore, if medical devices display a poor degree of accuracy, this may lead to an inappropriate diagnosis and treatment plan for the patient, potentially costing money and resulting in poor patient outcomes. In a 2015 study, researchers looked into comparing the accuracy of 4 single-lead portable ECG devices with the standard 3-lead hospital cardiac device. Several physicians, known as reviewers, "performed rhythm interpretation and ECG signal quality assessment of the portable ECG device rhythm strips" (Mehta et al., 2015, p.711) with the signal quality determined based on the factors of baseline sway, artifact, and interpretability (Mehta et al., 2015). The results showed disappointingly poor performance of the portable, four single-lead ECG device as "over 40% of the portable ECG rhythm strips were classified as uninterpretable" (Mehta et al., 2015, p.715). However, the study notes that there was a low rate of rhythm misinterpretation when comparing the rhythm strips between the portable ECG and the hospital cardiac monitor. In its discussions of the patient's perceptions of the ECG, the study mentions that patients did not receive adequate training with the portable ECG device and the manufacturer instructions "were insufficient to allow patients to operate any of the portable ECG devices in a limited time," with a potential remedy being "instructional videos to demonstrate correct device operation" (Mehta et al., 2015, p. 710). In a 2021 study, researchers investigated the accuracy of

a non-12-lead ECG and photoplethysmography (PPG) in detecting Atrial Fibrillation (AF) by conducting a meta-analysis of 16 relevant studies encompassing 3217 participants and 7623 assessments. The estimated sensitivity and specificity of non-12-lead ECG and PPG for the detection of AF were reported 89.7% and 95.7%. Moreover, the automatic interpretation of non-12-lead ECG and PPG measurements was 94.7% and 97.6% respectively (Yang et al., 2021). The study concludes that additional validation is needed for assessing diagnostic accuracy and automatic analysis, before designating non-12-lead ECG and PPG as a new pre-screening option. Pre-screening does not preclude the requirement to use the more expansive golden standard 12-lead ECG diagnostic and physician interpretation.

At-Home vs. Medical-Grade ECG Devices

CVDs can potentially become more accurately diagnosed, controlled, and prevented by utilizing continuous non-invasive monitoring of the heart (Serhani et al., 2020). Analysis of ECG signals along with other biological signs serves as one of the best methods to pursue the detection and prevention of Atrial Fibrillation leading to a stroke event. In the past few years, medical-grade ECG monitoring systems have been broadly adopted by the healthcare sector (Bansal & Joshi, 2018; Sanghavi, 2018). Medical-grade ECG provides accurate monitoring though there are few differences among the various ECG medical-grade devices in terms of cost, size, weight, industry certification, sensitivity, duration of recording, and degree of accuracy. The top ECG medicalgrade devices currently in use include the 12-lead ECG, multichannel ECG (MECG), Holter monitor, and implantable loop recorder (ILR). The golden standard for ECG is the popular 12-lead ECG in which wires are attached to electrodes positioned at 10 locations on the body (Macfarlane & Lawrie, 1989; Steijlen et al., 2018). The MECG body surface mapping systems assess simultaneously across 10 positions on the body utilizing many ECG leads and analyzing the waveform shapes. Thus, MECG has proven to boost the accuracy of the diagnosis (Marcinkevics et al., 2018). The standard 12-lead ECG and the MECG systems are mostly utilized for short-term ECG monitoring. For long-term ECG monitoring, the Holter monitor has been mostly utilized as an at-home device since the 1960s. Though small in size, these devices and cables are uncomfortable to wear. The device can record high-quality single or multi-lead ECG over 14 days. An implantable long-term monitoring ECG is the wireless ILR that is inserted under the skin, though it requires frequent visits to the office given its limited recording capacity.

Over the last five years, single-lead, handheld ECG devices and smartphone-based ECG monitors have been increasingly adopted. Such devices utilize a built-in algorithm that distinguishes between normal ECG and arrhythmias. Though single-lead ECGs do not always show P waves, patients find them easy to use, accessible, and fast (<30 Seconds). To provide accurate diagnosis single-lead ECG devices require low-noise high-quality signals which may not always be available when patients perform the ECG recording. Consequently, a repeated test using a 12-lead ECG followed by a cardiologist review may be necessary to confirm Atrial Fibrillation (AFib) diagnosis (Garabelli et al., 2017; Zywietz & Willems, 1987). Despite the tradeoffs of high sensitivity and lower specificity, the use of smartphones to record and transmit ECG data expanded new opportunities for real-time arrhythmia diagnosis and cardiac monitoring. Additional challenges associated with medical-grade ECG monitoring include the need for remote technical support as patients and their caregivers may not have the skills necessary to set up the ECG monitoring device, calibrate it frequently, as well as transmit wirelessly the data from the device to an app via

a smartphone or a tablet. Another challenge relates to the artifact noise level interference that is picked by the ECG electrodes interfering with the ECG signal. The higher the noise level the higher the distortion to the ECG signal making the reading and interpretation of the ECG data inconclusive. Artifact noise may be attributed to poor or even loose contact between the ECG electrode and the skin. Low-frequency noise stems from baseline wander, motion interference, or respiration. Thus, causing a baseline drift, resulting in a marked distortion of repolarization that may produce inaccurate ST-segment deviation. High-frequency noise may be attributed to muscle contraction, powerline, or radiated electromagnetic interference. Knight et al. (1999) recounted the clinical consequences of misdiagnosis due to noise leading to unnecessary cardiac catheterization, medical therapies (intravenous antiarrhythmic agents), as well as implantation of a permanent pacemaker. Thus, researchers and manufacturers recommend providing basic training to patients, their caregivers, and professional healthcare staff on how to properly operate the ECG Monitoring device, and placement of the ECG leads followed by these individuals demonstrating that can properly set up the ECG device and properly conduct the ECG reading. Moreover, initial ECG measurement to establish a baseline, and periodic office visits are recommended to enable accurate assessment as well as data comparison over time (Drew, 2006; Rashkovska et al., 2020).

Methodology

New technological advances in home care and telemedicine have produced several new tools that aid in managing chronic patient care at-home as well as post-hospitalization. Consequently, lowering healthcare costs prevents serious complications from occurring, and readmission. This research focuses on at-home ECG (see Figure 1), a relatively new and promising technology where patients are given the tools to take an ECG measurement within the comfort of their own home, supporting the home hospital model. However, sometimes the ECG data that is produced is unreadable or inaccurate because of various challenges that patients face. While the device itself is a hospital-level medical-grade 12-Lead ECG with significant clinical accuracy, the data collection process may impact the ECG results causing the data to be inaccurate such as ECG data with noise but still interpretable (Level 3), or unusable such as ECG data with noise that is uninterpretable (Level 2) or even flatline (Level 1). When inaccurate ECG data is collected by the patient or their caregiver (Levels 1 or 2), the cardiologist's recommendations for the patient can be impacted, potentially putting the patient at risk. This study sought to identify these problems and propose targeted solutions to maximize the effectiveness of this promising technology. The unit of analysis in this study was the ECG data readability taken by the patient or their caregivers at-home, while compared with a control group of patients whose ECG measurement was taken by a qualified healthcare professional using the same 12-lead ECG device.

Online Journal of Applied Knowledge Management

A Publication of the International Institute for Applied Knowledge Management

Volume 11, Issue 1, 2023

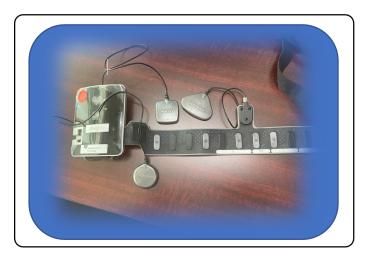


Figure 1. Picture of the Novel At-Home Medical Grade 12-Lead ECG

The device utilized to record ECG data refers to the E483 Smart Heart 12-lead ECG. ECG recorded data was obtained and reviewed anonymously by a team of cardiologists, ECG technicians, and Health Informatics specialists who then categorized the ECG data into the five levels of accuracy: Level 1 – "Flatline (FL)"; Level 2 – "Noise: uninterpretable"; Level 3 – "Noise: interpretable"; Level 4 – "Acceptable"; and Level 5 – "Good quality" (See Figure 2).

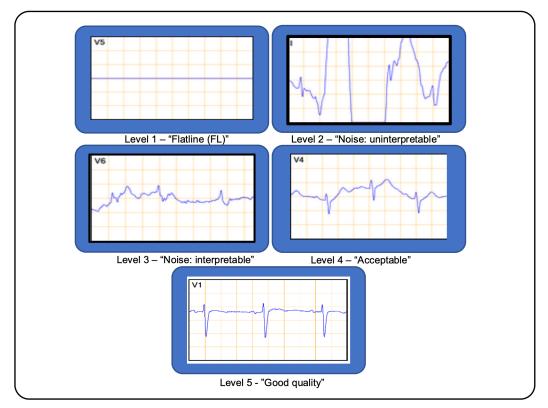


Figure 2. The Five Assessment Levels with Examples from At-Home ECG Data

The ECG data records were obtained from 20 patients ages 54 to 86 years old, with an average age of 68 years old. All patients had their first ECG recorded at the clinic by a healthcare professional during onboarding and then provided initial training along with their caregiver on how to conduct the ECG at-home. All the additional ECG measures were conducted at-home by the patients or their caregivers. All of the patients are considered "complex" indicating that they have a diagnosis of two to eight chronic diseases, where all patients are diagnosed with the minimum of Congestive Heart Failure and chronic obstructive pulmonary disease. ECG recordings from 2020-2022 were collected and transmitted to the clinic via a proprietary online platform. Participants were required to take their ECG readings on a weekly and as-needed basis at-home. The data was then coded by a team of cardiologists, an ECG technician, and three Health Informatics specialists for each of the 12-lead results based on the five levels of accuracy as seen in Figure 2. The data was coded into Excel for the data analyses. Average accuracy levels were then calculated across each reading period across all 12-leads along with standard deviation (St.Dev).

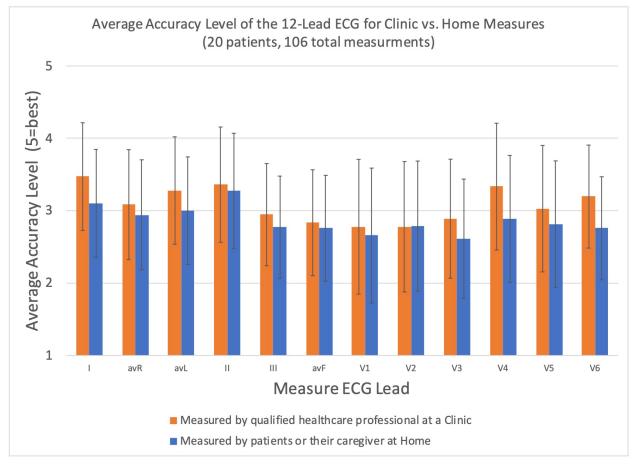
Results

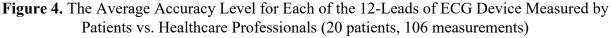
The results of such testing are presented in Figure 3 where the initial impression is that while the device is the same device across measures, the accuracy level of the ECG 12-leads data taken by a qualified healthcare professional at the clinic appears to be higher, representing more accurate reading (mean=3.08, St.Dev.=0.608) compared to data taken by the patient (mean=2.86, St.Dev.=0.654). Data were then analyzed with SPSS version 27 for Analysis of Variance (ANOVA) comparing the two sets of measurements. Results indicate that there is no significant mean difference (F=2.557, p=0.113) between the two sets of measures.



Figure 3. The Overall Average Accuracy Level of ECG Data Measured by Patient vs. Healthcare Professional (20 patients, 106 measurements)

The results indicate that H1 is not rejected given that there is no statistically significant mean difference between the accuracy level of ECG data taken by patients, or their caregivers compared to those taken by qualified healthcare professionals. Additionally, mean scores were calculated for each of the 12-leads for the two sets of measurements. Results presented in Figure 4 appear to indicate that five of the 12-leads (III, avF, V1, V2, and V3) provided less than desired results for the measures conducted by qualified healthcare professionals, while seven of the 12-leads (avR, III, avF, V1, V2, V3, V4, V5, and V6) provided less than desired results for the measures conducted by the patients with under Level 3 on average.





Additionally, ANOVA was conducted comparing all 12-leads between the two sets of data (measures conducted by qualified healthcare professionals vs. measures conducted by the patient). Results indicated that three of the 12-leads (I, V4, and V6) were statistically significant at p<0.05 as indicated in Table 1. These results indicate that H2 is partially rejected. While the device itself used at home is a hospital-level medical-grade with clinical accuracy, it is the placing of the 12-leads and the lack of proper training on how to properly use the at-home ECG that may cause such average accuracy in the results. We also anticipate that the external leads will have a higher degree of ECG data readability compared to the internal leads.

To address H3, ANOVA was conducted comparing all measures based on the number of diagnoses patients have. Results indicated that there is a statistically significant mean difference (F=5.235, p=0.007) in the accuracy level of the 12-leads as patient diagnoses increase in complexity, with diagnosis complexity characterized by the number of complex chronic diseases diagnoses, which increases from 2 to 8 as indicated in Table 2.

Table 1: ANOVA Results for ECG Measures Conducted by Qualified Healthcare Professionals at the Clinic vs. Patients or their Caregivers at-home (20 patients, 106 measurements)

| ECG Lead | Measured by qualified healthcare professional at a Clinic | | Measured by patients or their caregiver at Home | | ANOVA | | |
|--------------------|---|--------|---|--------|-------|---------|--|
| | Average | St.Dev | Average | St.Dev | F | Sig. | |
| I | 3.472 | 0.941 | 3.100 | 0.745 | 4.945 | 0.028 * | |
| avR | 3.083 | 0.806 | 2.943 | 0.759 | 0.780 | 0.379 | |
| avL | 3.278 | 0.815 | 3.000 | 0.742 | 3.116 | 0.080 | |
| П | 3.361 | 0.867 | 3.271 | 0.797 | 0.283 | 0.596 | |
| Ш | 2.944 | 0.860 | 2.771 | 0.705 | 1.229 | 0.270 | |
| avF | 2.833 | 0.737 | 2.757 | 0.731 | 0.257 | 0.613 | |
| V1 | 2.778 | 1.017 | 2.657 | 0.931 | 0.375 | 0.542 | |
| V2 | 2.778 | 0.989 | 2.786 | 0.899 | 0.002 | 0.967 | |
| V3 | 2.889 | 0.887 | 2.614 | 0.822 | 2.515 | 0.116 | |
| V4 | 3.333 | 0.986 | 2.886 | 0.877 | 5.689 | 0.019 * | |
| V5 | 3.028 | 1.028 | 2.814 | 0.873 | 1.258 | 0.265 | |
| V6 | 3.194 | 1.009 | 2.757 | 0.711 | 6.706 | 0.011 * | |
| Overall 12-Lead | 3.081 | 0.654 | 2.863 | 0.608 | 2.902 | 0.091 | |

* p < 0.05; ** p < 0.01; *** p < 0.001

Table 2: ANOVA Results for ECG Measures by Number of Diagnoses of Complex Chronic Diseases (20 patients, 106 measurements)

| | ANOVA | | | | | | | | | | | |
|---------|--------|------------------|--------|------------------------|--------|-------|-------|----|--|--|--|--|
| 2 only | | 3 to 4 diagnoses | | 5 or more diagnoses | | | | | | | | |
| Average | St.Dev | Average | St.Dev | Average | St.Dev | F | Sig. | | | | | |
| 3.27 | 0.650 | 2.86 | 0.555 | 2.79 | 0.660 | 5.235 | 0.007 | ** | | | | |
| | | | | | | | | | | | | |

* p < 0.05; ** p < 0.01; *** p < 0.001

Online Journal of Applied Knowledge Management

A Publication of the International Institute for Applied Knowledge Management

Volume 11, Issue 1, 2023

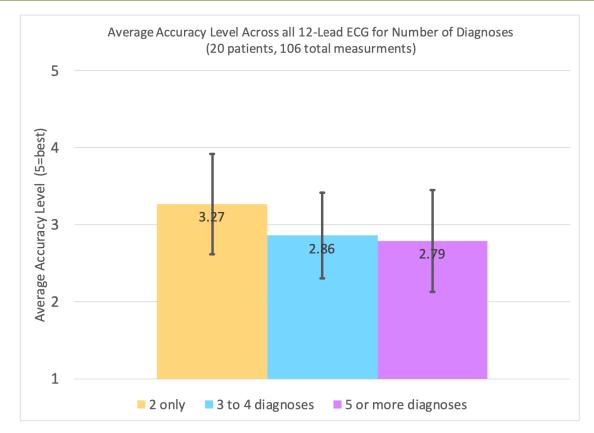


Figure 5. The Overall Average Accuracy Level for ECG Data Measured by Patient Number of Diagnoses of Complex Chronic Diseases (20 patients, 106 measurements)

Discussion

Overall, the ECG data did not support a statistically significant mean difference between the accuracy level of ECG data taken by patients, or their caregivers compared to those taken by qualified healthcare professionals (H1), thus indicating that patients and their caregivers appear to be able to take a proactive role in their disease management. Still, the results indicate a potential to improve the ECG data to a higher quality of readability. Patients can also impact precision public health by consenting to share their own ECG data with researchers developing clinical-decision support applications. Large-scale ECG data collection may potentially lead to discovering a more effective cardiovascular disease management path for individual patients (Ginsburg & Phillips, 2018).

The results of the ANOVA comparing all 12-leads between the two sets of data indicated that H2 is partially rejected, thus, five (III, avF, V1, V2, and V3) of the 12-leads provided less than desired results for the measures conducted by qualified healthcare professional (as seen in Figure 4), while nine of the 12 provided less than desired results for the measures conducted by the patients with weak ECG data readability on average. Furthermore, the ANOVA results comparing all measures based on diagnosis complexity significantly supported this conclusion, thus, patients with a higher

number of complex chronic disease diagnoses tend to produce ECG data that has weak ECG data readability on average.

The results of this research study noted above will aid healthcare professionals in determining which aspects, such as placement of leads or quality of instructions, of the at-home ECG device need to be improved to produce the best degree of ECG readability possible so that cardiologists can interpret the results correctly. While at-home medical technologies are developing even to the level of medical-grade, it is the training part and the experience that are lacking in non-professional healthcare. Moreover, results indicate that further research is needed to assess the effectiveness of training and coaching about medical measurements conducted at-home by the patients and their caregivers.

One of the study's weaknesses includes a lack of patients' adherence to taking weekly ECG recordings and uploading the ECG data to the platform supported by the informatics clinic team. The variability of patients' ECG recordings could potentially impact the accuracy and readability of the data. Consequently, this could interfere with the benefits of using at-home ECG technology to reduce admissions and encourage patients to be more proactive in monitoring their health. Another weakness arises from patients' reluctance and hesitance to visit the clinic or invite certified ECG technician staff to take an ECG reading during the COVID-19 pandemic. Continuing the study post-COVID-19 pandemic will provide more opportunities for clinic visits as well as ECG technician staff home visits where patients and their caregivers can seek advice about proper handling techniques of the ECG at-home device.

Additional research is needed to assess the role of improved training and proper placement of the 12-leads, on the ECG accuracy level. We also hope that such improvements can lead to appropriate early interventions and better health outcomes. Future research can build on the results of this study by designing a specific educational training video on the utilization of the at-home ECG device. After providing participants with an accessible training video, we hypothesize that the newly collected data will demonstrate improvements in ECG readability and accuracy. With proper utilization of this novel technology, patients can take control of their health, and become more confident in their abilities to produce high-quality, readable ECG data (Levels 3, 4, or 5, See Figure 2) to manage their chronic CVD. Furthermore, stakeholders will recognize that the at-home ECGs not only potentially save money on repetitive hospital admissions but also allow for better resource utilization by allowing increased availability of hospital beds needed to treat other ill patients. This captivating healthcare technology has strong potential to decrease hospitalization rates, decrease stress for patients and caregivers, as well as provide a higher quality of life for patients.

Acknowledgment

The authors wish to thank the staff at Duxlink Health Medical Centers in South Florida for their collaboration on this research project and their outstanding contribution to the success of this project. This research project did not receive any outside funding and the authors wish to declare no conflict of interest with the manufacturer of the ECG devices.

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Authors Biographies

Michelle M. Ramim, Ph.D., MBA is an Assistant Professor, and the Director of the Bachelor of Science in Health Informatics program at Nova Southeastern University, Dr. Kiran C. Patel College of Osteopathic Medicine, Department of Health Informatics. She has over 30 years of experience in the healthcare field and extensive experience as an Information Technology (IT) consultant for small and mid-size organizations. She has directed the development and implementation of several IT projects in the healthcare field and held a license as



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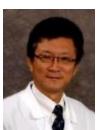
Janavi Patel is a second-year medical student at the Nova Southeastern Dr. Kiran C. Patel College of Osteopathic Medicine. She has presented research on electrocardiogram readability virtually at KM's international conference in 2022. Janavi serves on the board of various clubs at NSU-KPCOM including the Pain Medicine and Rehabilitation Club, the Student Osteopathic Association for Research, and Entrepreneurs in Healthcare. As an aspiring physician, Janavi hopes to stay involved in research and collaborate with professionals from all aspects of healthcare to make a tangible difference in the local and global community.

Colin Pulickathadam is a second-year dual enrolled, pre-medical undergraduate student at Nova Southeastern University (NSU) studying to obtain his bachelor of science (B.S.) degree in health informatics through the Dr. Kiran C. Patel College of Osteopathic Medicine (KPCOM). He has presented research on electrocardiogram readability at the global Healthcare Information and Management Systems Society (HIMSS) conference, NSU's Undergraduate Student Symposium (USS), KPCOM's Undergraduate Student Symposium, and virtually at KM's international conference in 2022. Colin is also an active member

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Michael Shen, MD is a practicing cardiologist with four board certifications and expertise in healthcare IT, EMR/device integration, and utilization analytics. He has enriching working experience in both the technology industry and clinical care for over 25 years. Dr. Shen owns 8 patents in analytical methods, device/microchip designs, and newly integrated care processes with telemedicine. Under his leadership, Duxlink Health has been ranked as the "10 Most Promising Healthcare Tech Startup 2019" by CIO Review and "The 10 Best Performing TeleHealth Solution Providers in 2019" by Insight Care.

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