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Structural Heart Abnormalities are Prevalent on the 12-lead ECG among Volunteer Firefighters

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Clinical Significance

Conduction abnormalities and other cardiac conditions, identifiable on resting 12-lead ECGs, are prevalent among firefighters. ECG is an accessible, non-invasive tool that can helps pinpoint higher-risk individuals, especially in rural areas that depend on volunteer services. Identification of these prevalent risk factors may be useful in further cardiac risk stratification.

Abstract:

Objective: Sudden cardiac death (SCD) is the leading cause of death among on-duty firefighters in the U.S. This study aimed to determine the prevalence of pathoanatomical substrates related to SCD in a cohort of firefighters over 9 years using 12-lead electrocardiogram (ECG) screening.

Method: Twelve-lead ECG was collected from 2011-2019 as part of a health program. Measurements (e.g., QRS duration) and interpretation statements (e.g., left ventricular hypertrophy) were obtained using automated software (MUSE, GE Healthcare). Descriptive, comparative, and longitudinal analyses were performed ($p<0.05$).

Results: A total of 1,041 firefighters (mean age=47.1±13.6) were screened, recording 3,142 ECGs. Among the ECGs (n=465), 42.6% (n=198) had conduction abnormalities, and 14.2% (n=66) with coronary disease indicators. There were no time-dependent changes.

Conclusions: Routine 12-lead ECGs could help detect asymptomatic structural heart defects that may increase the risk of SCD among firefighters.

Keywords

Sudden Cardiac Death, 12-lead Electrocardiogram, Firefighters, Emergency Responders, Mass Screening, Occupational Health, Occupational Health Services, Occupational Health Nursing

Bulleted Learning Outcomes

After completing this enduring educational activity, the learner will be better able to:

- Evaluate how underlying cardiac conditions identified on the resting 12-lead electrocardiogram (ECG) are highly prevalent among the fire service
- Explain how chronic cardiac conditions detectable via ECG contribute to increased SCD risk in high-stress occupations like firefighters
- Analyze how abnormal cardiac measures on the resting 12-lead ECG change over a 9-year period

Introduction:

In the United States (US), the most common cause of death among on-duty firefighters is sudden cardiac death (SCD)[1,2]. SCD occurs when a ventricular tachyarrhythmia ceases cardiac output leading to sudden death[3]. Firefighters are at higher risk of SCD compared to other first responders and the general public due to their strenuous and stressful occupation compounded by high rates of underlying cardiometabolic diseases[1,2]. Our team's previous publication in the journal *Workplace Health & Safety* identified volunteer firefighters as being at the greatest risk of SCD compared to career and wildland firefighters, and identified New York State (NYS) as the state with the highest prevalence of SCD among firefighters in the nation[4]. Volunteer firefighters were differentially affected by SCD[4].

Chronic pathoanatomical substrates such as ventricular hypertrophy and conduction diseases within the heart are known to cause ventricular tachyarrhythmias that can cause SCD[5,6]. Importantly, such chronic pathoanatomical substrates can be identified with the standard 12-lead, 10-second electrocardiogram (ECG)[5,6]. For example, hypertrophy can be observed as exacerbated R and S wave amplitude, coronary artery disease can be observed as changes in the ST-segment and T wave[7], and cardiac conductive disorders are reflected as prolongation of the QRS duration[8]. Given that the 12-lead ECG is relatively inexpensive and aligns with current screening strategies recommended by the National Fire Protection Association (NFPA)[9], its recording may help identify firefighters at greater risk of SCD.

The objectives of this study were to (1) Assess the prevalence of pathoanatomical substrates identified from the 12-lead ECG that may propagate to ventricular tachyarrhythmias and cause SCD and (2) Assess any changes in the prevalence of pathoanatomical substrates and ECG features collected from the 12-lead ECG over a 9-year period. All the data were collected from an Occupational Health Screening Program that provided occupational health screenings that include 12-lead ECGs to firefighters in one rural county in Upstate New York. The rural county was almost entirely supported by volunteer firefighters, other than 1 career department. We specifically worked with this Occupational Health Screening Program because (1) NYS has the highest prevalence of SCD in the United States and (2) Upstate New York is almost entirely reliant on volunteer firefighters for fire protection services.

Methods:

Data Sharing

All data was collected by the Occupational Health Screening Program, and de-identified before being shared through a formal data sharing agreement with the University of Rochester. The paper 12-lead ECG, as well as age and sex, were routinely collected and shared with the University of Rochester for analysis. All analyses were retrospective in nature and completed at the University of Rochester. Since the analysis was conducted retrospectively using data not originally collected for research purposes, a waiver of informed consent was granted. This study was reviewed and approved by the Institutional Review Boards of the participating organizations. The study was supported by UNYTE Translational Research Network Grant, part of UL1TR002001, and internal research support grant. This study aligned with the Strengthening the reporting of observational studies in epidemiology (STROBE) guidelines[10]. Please see the Supplementary Digital Content, http://links.lww.com/JOM/B915.

Data Collection and Description through the Occupational Health Screening Program

Current recommendations published by the NFPA and Occupational Safety and Health (OSHA) recommend and in some cases mandate routine health screening[9,11]. The Occupational

Health Screening program follows NFPA recommendations for the frequency of physicals, including 12-leads ECGs[9]. While such guidelines are specifically directed towards NYS standard Class A and B firefighters, or those with significant exposure to fire and moderate-to-heavy workloads, many occupational health programs screen all classes of firefighters[9]. NYS standard class, screening frequency and number of firefighters for each NYS standard firefighter class are provided in Table 1 and Figure 1.

The Occupational Health Screening Program contracts with area fire departments to provide health screenings in compliance with medical clearance to serve as a firefighter. During a health screening, program staff, who are medical assistants, technicians, nurses and health care providers, visit the fire house or other location to screen career firefighters from that fire department. Screenings include a physical examination, a resting 12-lead ECG compliant with NFPA recommendations and completion of medical history and work-related questionnaires[9].

For this study, we specifically focused on the 12-lead ECGs. 12-lead ECGs were collected by using a portable 12-lead ECG Machine (MAC ECG Device, General Electric Healthcare, Chicago, IL). The 12-lead ECG was recorded in a private area of the firehouse with the firefighter in a supine and resting position. Electrodes were placed according to standard 12-lead ECG configurations, with the four limb leads placed on the arms and legs and the six precordial leads (V1 to V6) positioned across the chest. The sampling frequency (500 Hertz) and specific electrode types were consistent with typical clinical ECG practices. Before collection, firefighters remained in a resting position though the exact duration was not explicitly specified. The 12-lead ECGs were automatically interpreted by the General Electric Marquette 12SL ECG analysis program (General Electric Healthcare, Chicago, IL) and then reviewed by a health care provider before the firefighter left the screening. Paper copies of 12-lead ECGs with the interpretations were scanned into portable document format (PDF). Later, PDF were de-identified, assigned a study ID, and shared with the University of Rochester. All PDF format 12-lead ECGs were manually inspected by 2 nurse scientists (MGC and DJD). No 12-lead ECGs were deemed to have excessive noise or artifacts, so all were analyzed. We extracted interpretation summaries and automatic measurements from PDF files and converted them into a structured, analyzable comma-separated values (CSV) format using Python code integrated with optical character recognition (OCR) software from Nanonets (Nanonets, San Francisco, CA)[12]. OCR, a form of artificial intelligence, enables the conversion of text from images into discrete data elements, allowing automated extraction of relevant information. Our custom code, which is publicly available on GitHub, ensured transparency in data processing. The OCR software achieved an 82% accuracy rate in extracting interpretation summaries and automatic measurements into specific variables within the CSV file. To ensure accuracy and mitigate errors, two authors (AWB and DJD) manually reviewed and compared the extracted data against the original PDF files, verifying the correctness of both clinical statements and measurements. If discrepancies were identified, the authors corrected the extracted values by referencing the original ECG reports. Since all PDF files were already de-identified before processing, there were no ethical concerns or risks of privacy breaches associated with this method.

Data Preparation

We identified several conditions of interest due to their established association with sudden cardiac death (SCD) in prior studies[13,14]. These include non-specific intraventricular conduction abnormalities, vertical axis, right bundle branch block (RBBB), incomplete right bundle branch block, left bundle branch block (LBBB), left anterior fascicular block (LAFB), left posterior fascicular block, coronary artery disease or prior myocardial infarction, left ventricular hypertrophy (LVH), and right ventricular hypertrophy (RVH). According to the manufacturer and supported by peer-reviewed studies, the reported sensitivity and specificity for these conditions are as follows: RBBB (90% sensitivity, 100% specificity), LBBB (78% sensitivity, 99.9% specificity), LBBB with fascicular delay (88% sensitivity, 100% specificity), LVH using the Cornell Product criteria (11% sensitivity, 97% specificity), prior myocardial infarction (98.8% sensitivity, 99.5% specificity), and RVH (29.1% sensitivity, 100% specificity)[15-18].

To address the variability in screening schedules among firefighters, we established a requirement for inclusion: firefighters must have had at least three 12-lead ECGs recorded during the 9-year period from 2011 to 2019. This criterion allowed us to analyze cardiac rhythm, pathoanatomical substrates, and abnormal ECG features while accounting for potential changes in pathoanatomy, which often take significant time to develop and become detectable on a 12-lead ECG. Figure 2 illustrates the screening frequency for each firefighter. Based on this inclusion criterion, we excluded 12-lead ECGs from 576 firefighters who were screened only once or twice for the entire 9-year study period. We assess how the prevalence of the conditions changed over time.

For the longitudinal analysis, which aimed to assess changes in ECG measurements over time, we further refined the cohort to include 147 firefighters who had five or more 12-lead ECGs. Given that 12-lead ECG measurements are particularly sensitive to factors such as subject positioning and noise, this stricter requirement was designed to reduce variability, enhance rigor, and minimize the need for data imputation.

We imputed 28.4% of the data for the longitudinal analysis. We used linear interpolation to impute the data [19]. We choose this method because it preserves the inherent structure and variability of the data while minimizing potential bias[19]. Importantly, linear interpolation allowed us to maintain the integrity of the data distribution, as evidenced by our analysis: comparisons of both the means and distributions of ECG parameters before and after imputation revealed no statistically significant differences[19]. Table 2 shows p values for the T-test that was performed between datasets before and after imputation.

Statistical Analysis

We first analyzed the distribution of the data by computing the mean and standard deviations and produced histograms of the distributions. Based on the interpretation statements of ten pathoanatomical substrates which are early propagators of ventricular tachyarrhythmias leading to SCD, we counted the number of firefighters showing each pathoanatomical substrate. We computed the frequency (%) of abnormal 12-lead ECGs that laid outside of the established standards of normal range. We assessed how the prevalence of these substrates changed over time grouping 2011-2013 (Year 1), 2014-2016 (Year 2), and 2017-2019 (Year 3). Table 3 summarizes the description and normal range of each ECG measure[15]: 50bpm ≤ Heart Rate ≤ 100 bpm, 60ms ≤ P-Wave Duration ≤ 120ms, 120ms ≤ PR-Interval Duration ≤ 200ms, 350ms ≤ QT interval duration ≤ 470ms, 350ms ≤ Bazett-corrected QT interval duration ≤ 450ms, 80ms ≤ QRS complex duration ≤ 110ms, 0° ≤ P-Wave Axis ≤ +75°, -30° ≤ QRS wave axis ≤ +90°, -15° ≤ T wave axis ≤ +105°[20]. We performed longitudinal trend analysis using linear regression models with age and gender as covariates. All analyses were completed in Excel (Microsoft, Redmond, WA) and R Studio packages “dplyr”, “ggplot2”, “XLConnect” and “tidyr” (Posit, Boston, MA).

Results:

Sample Characteristics

In total, 1,041 firefighters representing 30 departments (29 volunteer departments and 1 career department) were screened through the Occupational Health Screening program of which 3,142 12-lead ECGs were recorded and digitized. Among those 2,057 12-lead ECGs from 465 firefighters, who were screened three or more times, were analyzed. Most of the sample was male (90.1%, n=419) with a mean age of 47.1 (SD=±13.6) years in 2011 (Figure 3). We compared age and sex between career (n=19, mean age=34.9±8.3, 100% male) and volunteer firefighters (n=446, mean age=46.1±13.8, 89.7% male). Age significantly differed between the two group (p<.01). For context, the NFPA reported that 89% of all volunteer firefighters were male with a mean age of 42 years. A large majority of the 12-lead ECGs (94.4%, n=1,941) were found to be in normal sinus rhythm and 5.6% (n=116) of the 12-lead ECGs were found to have an arrhythmia. Arrhythmias included 2.1% (n=44) of bradycardia arrhythmia (Heart Rate < 50 bpm) and 3.5% (n=72) of tachycardia arrhythmia (Heart Rate > 100 bpm) including atrial fibrillation, paced rhythms, and atrioventricular block (AVB) blocks. Prevalence of such pathoanatomical substrates were analyzed in the following part.

Pathoanatomical Substrates

Overall, 1,596 interpretation statements from 465 firefighters were generated and analyzed. Of these interpretation statements, 36.6% (n=584) were potentially indicative of underlying disease that may propagate SCD.

42.6% (n=198) of firefighters had a prevalent cardiac conduction abnormalities which included 23.0% (n=107) of non-specific intraventricular conduction disease, 7.96% (n=37) of vertical axis, 3.87% (n=18) of right bundle branch block, 3.23% (n=15) of left anterior fascicular block, 2.58% (n=12) of incomplete right bundle branch block, 1.72% (n=8) of left bundle branch block 0.22% (n=1) of left posterior fascicular block. Additionally, 14.2% (n=66) of firefighters had ECGs consistent with coronary artery disease or prior myocardial infarction, 4.30% (n=20) had left ventricular hypertrophy, and 1.51% (n=7) had right ventricular hypertrophy (Figure 4).

Distribution of ECG Parameters

The distribution of 9 ECG parameters including heart rate, QRS-axis, T-axis, QRS-axis, Bazett-corrected QT-interval duration (QTc-interval), QRS-wave duration, P-wave duration, PR-interval duration and P-wave axis are shown in Figure 5. There were a total 2.4% (n=50) abnormal heart rate, including 1.8% (n=36) bradycardia (<50 bpm) and 0.7% (n=14) tachycardia (>100 bpm). There was a total 20.2% (n=415) abnormal P-wave duration, 8.5% (n=175) abnormal QRS complex duration, 7.6% (n=156) abnormal PR-interval duration, 4.9% (n=101) abnormal QRS-wave axis, 4.1% (n=85) abnormal QT interval duration, 3.4% (n=70) abnormal Bazett-corrected QT interval duration, 3.1 % (n=64) abnormal P-wave axis, and 0.2% (n=5) abnormal T-wave axis (Figure 5).

Longitudinal Analysis

We first assessed changes in the prevalence of conduction abnormalities (Year 1 14.6%, Year 2 14.0%, and Year 3 14.4%), left ventricular hypertrophy (8.8%, 8.0%, 8.1%), right ventricular hypertrophy (1.0%, 0.9%, 1.1%), and coronary artery disease (5.6%, 8.5%, 8.2%). There were no statistically significant changes over time (p>0.05). We performed linear trend analysis to assess whether there were changes in the mean value in the ECG measures over time. We did not identify any statistically significant changes over time in each of the individual ECG parameters (p>0.05).

Discussion:

Our study found that nearly half of the firefighters exhibited ECG findings indicative of cardiac conduction abnormalities. Additionally, 14% had ECGs suggestive of coronary artery disease or prior myocardial infarction, 4% showed evidence consistent with LVH, and approximately 2% had findings indicative of RVH. Additionally, abnormal findings in P-wave duration (20.2%), QRS complex duration (8.5%), and PR interval duration (7.6%) were observed. These abnormalities may reflect underlying structural heart diseases, such as ventricular hypertrophy or ischemic heart disease, both of which are known to increase the risk of life-threatening arrhythmias that can cause SCD. Interestingly, our longitudinal trend analysis did not show significant changes in ECG parameters over time suggesting that these observed abnormalities may be chronic in nature rather than progressive.

To our knowledge, this is the first study which evaluated the prevalence of pathoanatomical substrates identified by NFPA-mandated 12-lead ECG screening. Al-Zaiti and Carey (2015) utilized 24-hour Holter monitoring to assess cardiac abnormalities in career firefighters who worked in a metropolitan city[26]. Their findings revealed that approximately 25% exhibited non-specific intraventricular conduction abnormalities, characterized by widened and fragmented QRS complexes[26]. Additionally, 12% showed evidence of coronary artery disease, identified through dynamic ST-segment depression, 7% had a prolonged QTc interval, and less than 5% presented with LBBB or signs of a prior myocardial infarction[26]. Their reported prevalence is consistent with what we reported here despite the differences in methodology.

We identified ten pathoanatomical substrates for this study based on prior evidence linking them to SCD among athletes, who engage in strenuous physical activities as do firefighters[13,14]. Established predictors of SCD in athletes, as outlined in the International Criteria for ECG Interpretation in Athletes Consensus Statement, include LBBB, signs of myocardial ischemia, and LVH/RVH, all of which warrant further investigation[13,14]. Notably, these guidelines emphasize caution when interpreting LVH/RVH due to the low sensitivity of ECG alone for these conditions, and this is consistent with our reported sensitivity and specificity[13-14,15-18]. With that said, some ECG markers such as LBBB, especially in the presence of symptoms are concerning and require further medical attention[21]. In the peer-reviewed manuscript we could find, a case review details the need to act when pathoanatomical substrates are identified on ECG among firefighters[22]. This case involved a 39-year-old male firefighter with LBBB who developed exertional dyspnea following a prolonged work session. While ECG and treadmill testing revealed only permanent LBBB, further investigations with echocardiography and myocardial scintigraphy did not provide additional insights[22]. However, multi-slice imaging significant stenosis in the mid-left anterior descending artery (LAD), which was confirmed by coronary angiography and successfully treated with coronary stenting[22]. Given the high prevalence of abnormalities highlighted in this study, alongside our prior evidence indicating a greater burden of coronary artery disease-related abnormalities among firefighters compared to athletes[23,24], further research is urgently needed to help develop treatment guidelines for firefighters.

One of the key strengths of this study is its large sample size, which allowed for a robust analysis of ECG abnormalities in a high-risk population of firefighters. The use of longitudinal data over a 9-year period provided valuable insights into the persistence and prevalence of cardiac conduction issues that may predispose individuals to SCD. Additionally, the study utilized a standard, widely accessible diagnostic tool (12-lead ECG) compliant with existing NFPA guidelines, making the findings highly relevant for clinical practice in both rural and urban settings. Another strength is the focus on volunteer firefighters, a group often underrepresented in health research despite being at elevated risk for cardiovascular events[4,18,19].

However, the study also has several limitations. One notable weakness is the reliance on retrospective data, which may have introduced bias due to missing data, or incomplete or inconsistent screening across participants. When conducting longitudinal analysis, gaps in the data had to be imputed, which, while necessary, may have impacted the accuracy of the findings. Furthermore, the study's reliance on mean imputation, although justified by the low variance in ECG parameters, might not fully capture the nuances of individual-level changes in ECG characteristics over time[18]. The study's focus on a single rural region that is primarily supported by volunteer firefighters limits the generalizability of the results to other regions and career firefighters[25].

Overall, our findings suggest a high prevalence of ECG abnormalities that could signal an increased risk of SCD in volunteer firefighters. Regular 12-lead ECG screenings can serve as a practical method to identify early propagators of ventricular tachyarrhythmias before they manifest as SCD among firefighters who may be at elevated risk for cardiac events[10]. When pathoanatomical substrates are identified on a 12-lead ECG, clinicians should conduct a comprehensive evaluation and advise the firefighter to follow up with their healthcare provider, particularly if symptoms are present. Depending on the specific abnormality, follow-up with echocardiography is a reasonable next step, as it is non-invasive, cost-effective, and provides detailed insights into myocardial function. Although echocardiography is not explicitly required by NFPA guidelines, its use aligns with the International Criteria for ECG Interpretation in Athletes Consensus Statement, which supports additional imaging when abnormalities are detected[9,13,14]. Incorporating these practices into routine screening protocols could enhance early detection and management of conditions associated with increased SCD risk, ultimately improving firefighter safety and health outcomes.

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Caption Section:

Figure 1. New York State standard classification of firefighters to class A (high intensity), B (moderate-high intensity), C (moderate-low intensity) and D (low intensity) in 2011-2019.

Figure 2. Number of firefighters for each screening frequency during the study period (2011 - 2019).

Figure 3. Age of firefighters in 2011, the first year of the study period (2011).

Figure 4. Number of firefighters with each pathoanatomical substrate. Left ventricular hypertrophy 4.30% (n=20), right ventricular hypertrophy 1.51% (n=7), coronary artery disease 14.2% (n=66), Cardiac conduction disease 42.6% (n=198), which includes non-specific intraventricular conduction disease 23.0% (n=107), vertical axis 7.96% (n=37), RBBB 3.87% (n=18), left anterior fascicular block 3.23% (n=15), IRBBB 2.58% (n=12), LBBB 1.72% (n=8), left posterior fascicular block 0.22% (n=1).

Figure 5. Graphical overview of distribution of 9 parameters measured from ECGs. Black solid lines represent the normal range of each parameter[15]. Any points outside of the black solid lines are abnormal. Different colors of the points represent different year when the data were obtained.

Table 1. Four New York State Standard Classes of Firefighters and Health Screening Frequency.

Table 2. P-values for T-test between datasets before and after imputation.

For all parameters, two groups have no statistical difference as p-value > 0.05.

Table 3. Standards of Normal Range of ECG Measures[15] Analyzed in this Study.

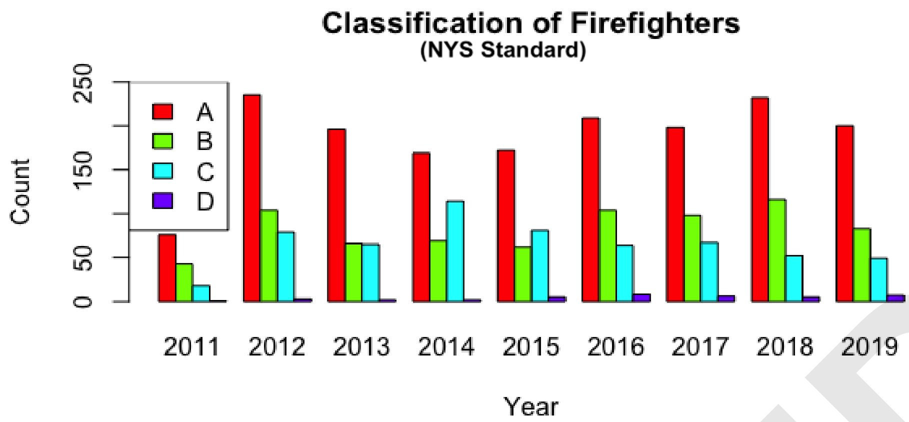


Figure 1. New York State standard classification of firefighters to class A (high intensity), B (moderate-high intensity), C (moderate-low intensity) and D (low intensity) in 2011-2019.

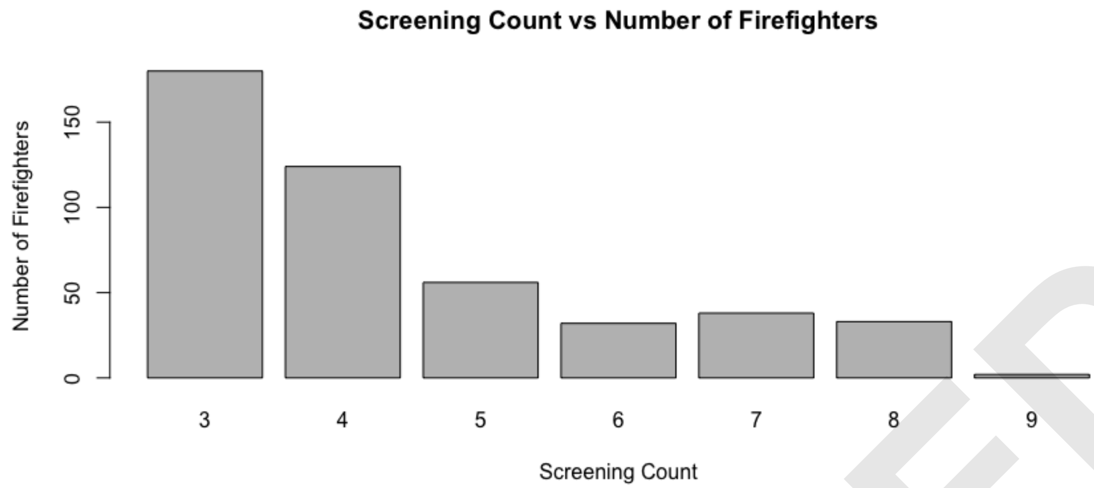
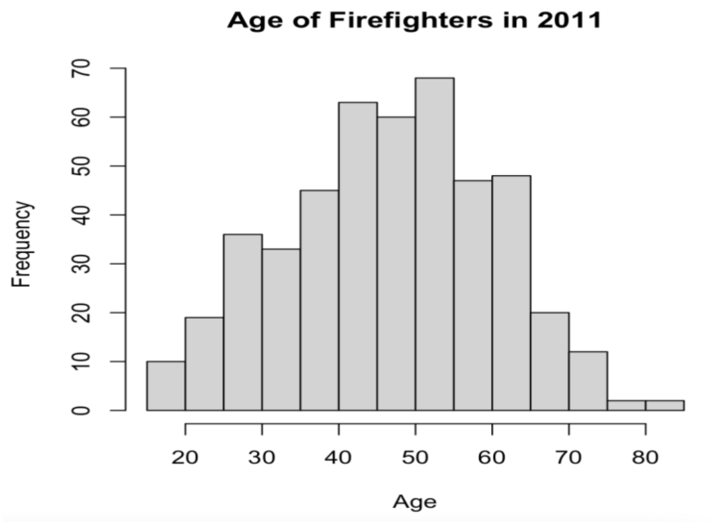


Figure 2. Number of firefighters for each screening frequency during the study period (2011 - 2019).



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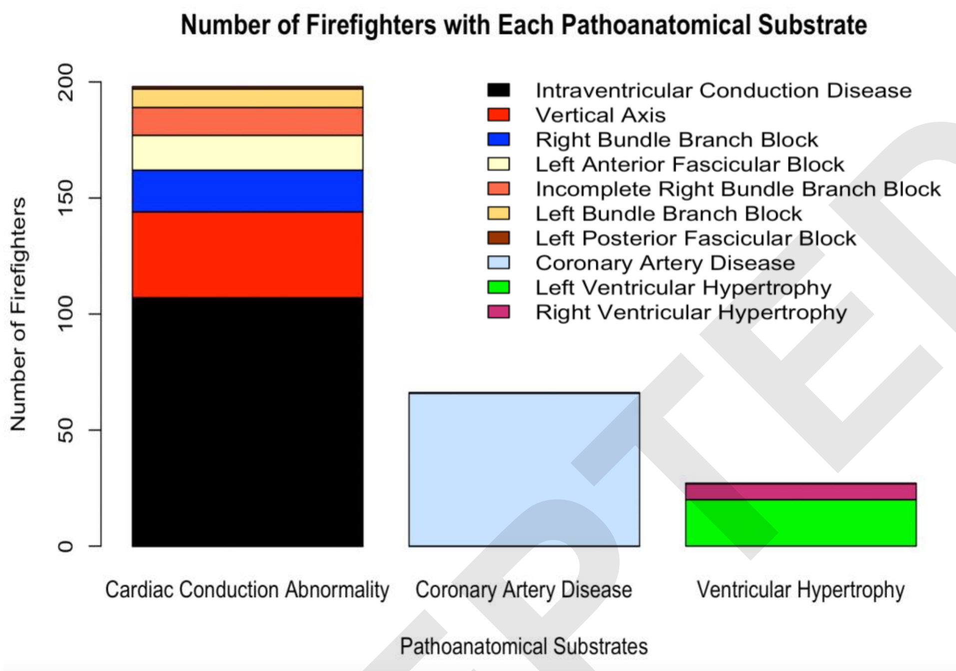
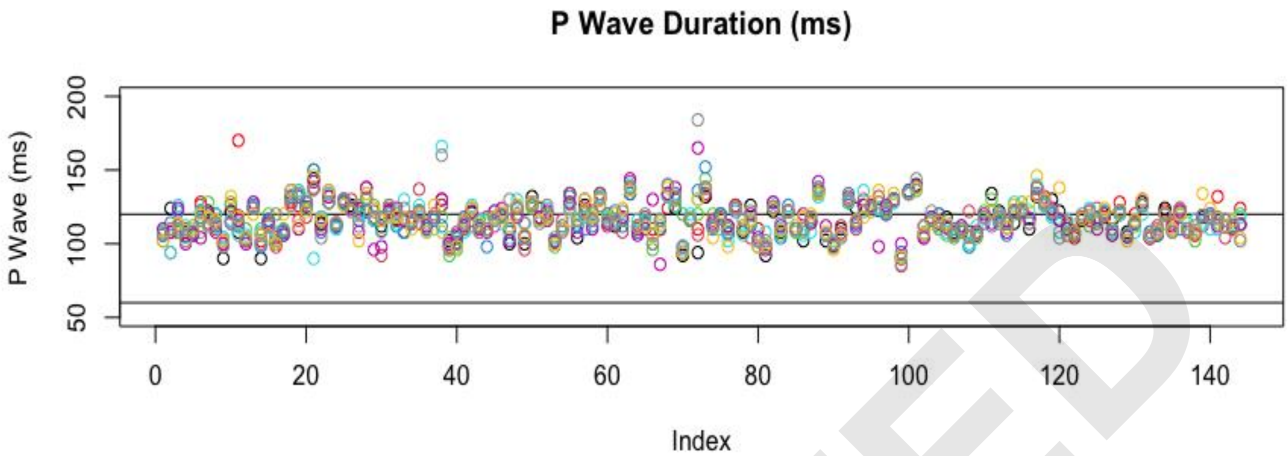
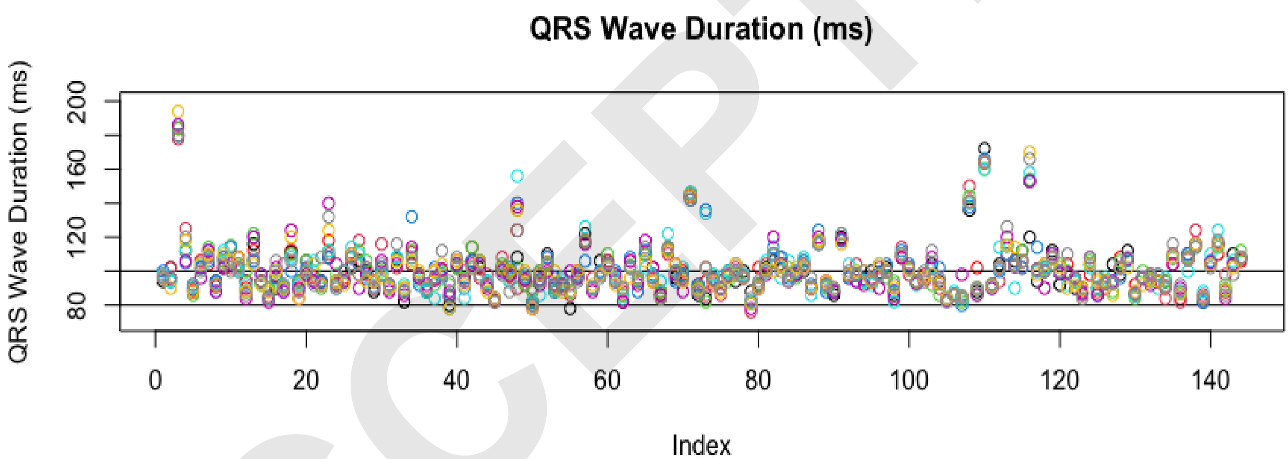
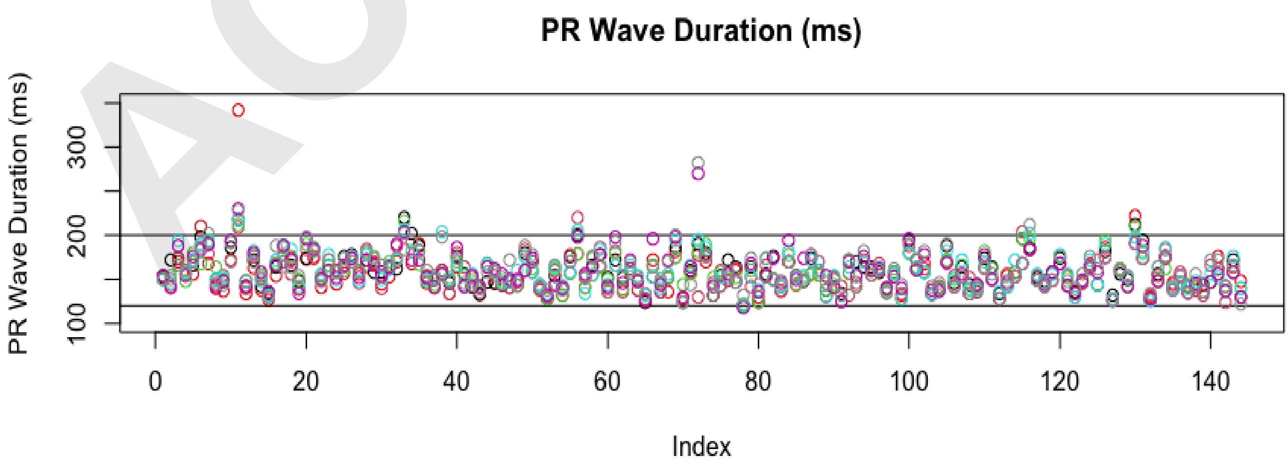
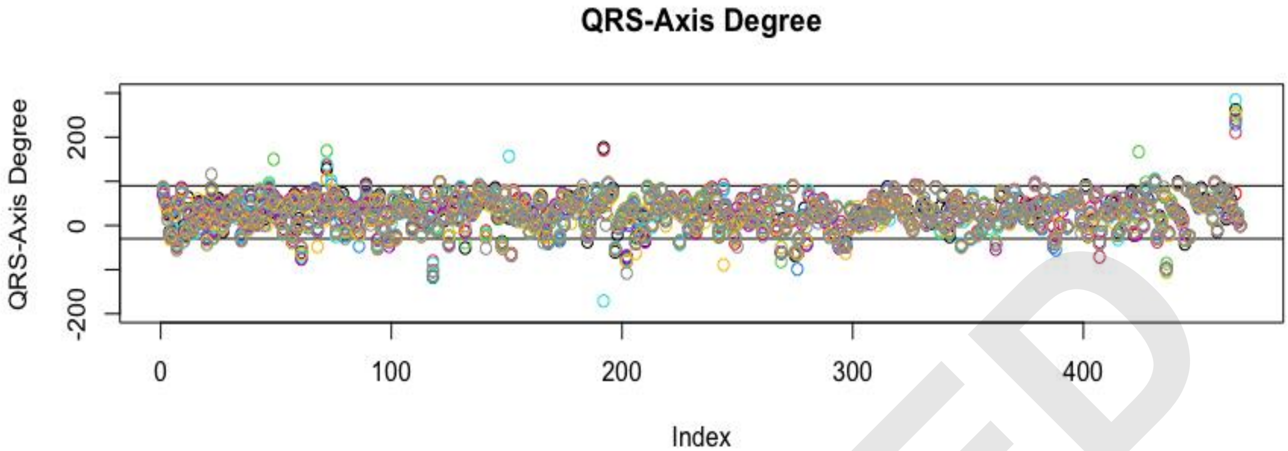


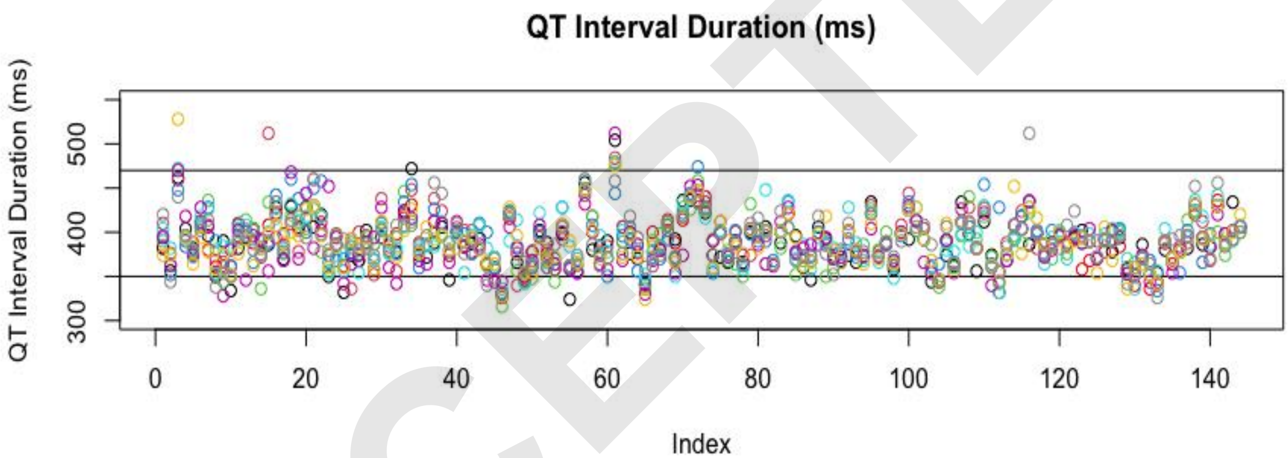
Figure 4. Number of firefighters with each pathoanatomical substrate. Left ventricular hypertrophy 4.30% (n=20), right ventricular hypertrophy 1.51% (n=7), coronary artery disease 14.2% (n=66), Cardiac conduction disease 42.6% (n=198), which includes intraventricular conduction disease 23.0% (n=107), vertical axis 7.96% (n=37), RBBB 3.87% (n=18), left anterior fascicular block 3.23% (n=15), IRBBB 2.58% (n=12), LBBB 1.72% (n=8), left posterior fascicular block 0.22% (n=1).

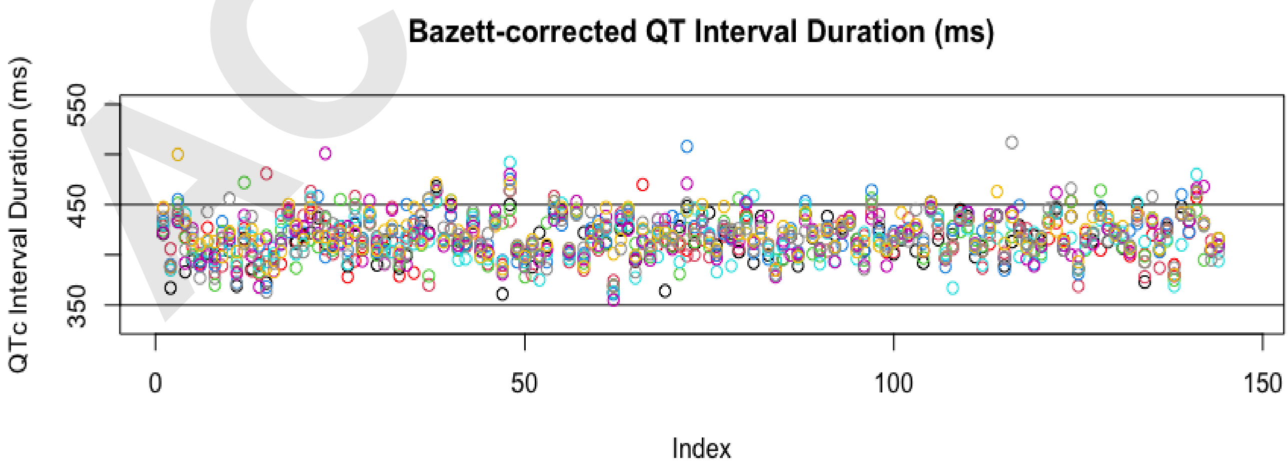

P Wave Duration (ms)
P Wave (ms)
50
100
150
200
0
20
40
60
80
100
120
140
Index


QRS Wave Duration (ms)
QRS Wave Duration (ms)
80
120
160
200
0
20
40
60
80
100
120
140
Index


PR Wave Duration (ms)
PR Wave Duration (ms)
100
200
300
0
20
40
60
80
100
120
140
Index


QRS-Axis Degree
QRS-Axis Degree
-200
0
200
0
100
200
300
400
Index


QT Interval Duration (ms)
QT Interval Duration (ms)
300
400
500
0
20
40
60
80
100
120
140
Index


Bazett-corrected QT Interval Duration (ms)
QTc Interval Duration (ms)
350
450
550
0
50
100
150
Index

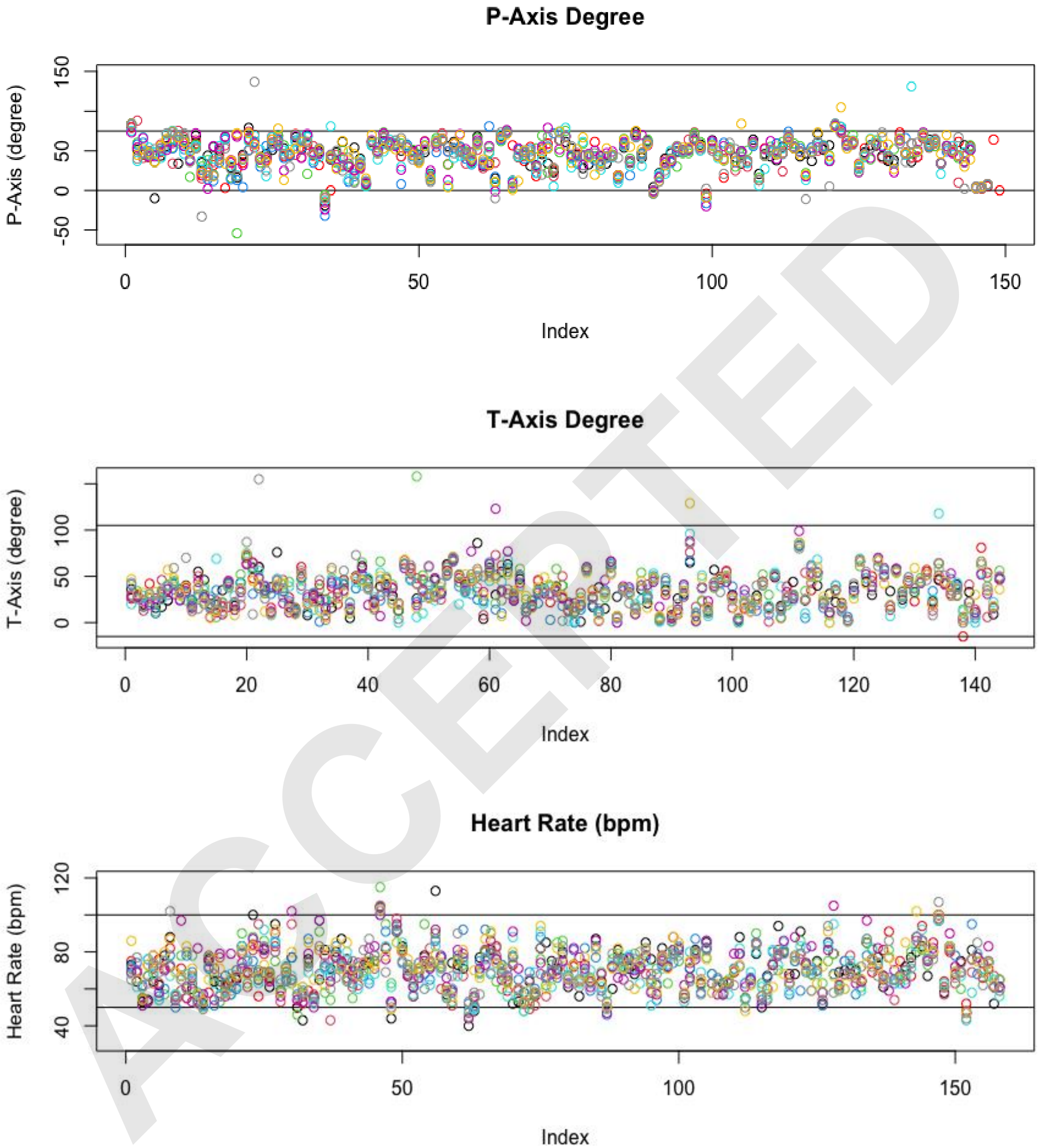


Figure 5. Graphical overview of distribution of 9 parameters measured from ECGs. Black solid lines represent the normal range of each parameter[15]. Any points outside of the black solid lines are abnormal. Different colors of the points represent different year when the data were obtained.

Table 1. Four New York State Standard Classes of Volunteer Firefighters and Health Screening Frequency.

Firefighters Class	**Description**	**Screening Frequency**
A	Interior Structural Firefighter No Restrictions Unlimited Respirator Use	Age>40: Annually 30<Age<39: Bi-annually Age<30: Tri-annually
B	Only Exterior Firefighter Light to Moderate Workload Use of Respirator for Emergency Short Term Use Only	Age>40: Bi-annually 30<Age<39: Tri-annually Age<30: Every 5 years
C	Support Firefighter Light Workload Only No Respirator Use	Age>50: Bi-annually 40<Age<50: Tri-annually Age<40: Every 5 years
D	No Firefighter Activities Auxiliary Work Only	-

Table 2. P-values for T-test between datasets before and after imputation.
For all parameters, two groups have no statistical difference as p-value > 0.05.

Parameter	P(T<=t) two-tail
Heart Rate	0.11
P Axis	0.88
P Interval	0.81
PR Interval	0.52
QRS Interval	0.75
QRS Axis	0.55
QT Interval	0.50
QTc Interval	0.97
T Axis	0.71

Table 3. Standards of Normal Range of ECG Measures[15] Analyzed in this Study.

Features	Description	Normal range
Heart Rate (beats per minute)	Number of times the heart beats within a minute.	50bpm ≤ Heart Rate ≤ 100 bpm
P wave duration (milliseconds)	Length of the P wave, the first positive deflection on the ECG representing atrial depolarization.	60ms ≤ P-Wave Duration ≤ 120ms
PR interval duration (milliseconds)	Length of the PR interval which represents the time between atrial depolarization and ventricular depolarization.	120ms ≤ PR-Interval Duration ≤ 200ms
QT interval duration (milliseconds)	Time from the start of Q wave to the end of T wave. Represents the duration of the ventricular action potential.	350ms ≤ QT interval duration ≤ 470ms
Bazett-corrected QT interval duration (milliseconds)	Corrected QT interval enabling comparison QT intervals of at different Heart Rates and at different time points within and between individuals.	350ms ≤ Bazett-corrected QT interval duration ≤ 450ms
QRS complex duration (milliseconds)	Duration of QRS complex. Represents the conduction speed in the ventricles.	80ms ≤ QRS complex duration ≤ 110ms
P wave axis (degree°)	Direction of P wave degrees that shows atrial depolarization.	0° ≤ P-Wave Axis ≤ +75°
QRS axis (degree°)	Net direction of all vectors generated by the depolarization waves of ventricular cardiomyocytes.	-30° ≤ QRS wave axis ≤ +90°
T wave axis (degree°)	Direction of T wave degrees that shows ventricular repolarization.	-15° ≤ T wave axis ≤ +105°
Cardiac rhythm	Record rhythmic activity of heart.	Normal sinus rhythm, Sinus Bradycardia, Atrial Fibrillation, Sinus Arrhythmia etc.
Clinical statements	AI generated clinical statements based on ECG record.	Wolff Parkinson White Syndrome, Right Bindle Branch Block, 1st Degree AV Block etc.

STROBE Statement—Checklist of items that should be included in reports of ***cohort studies***

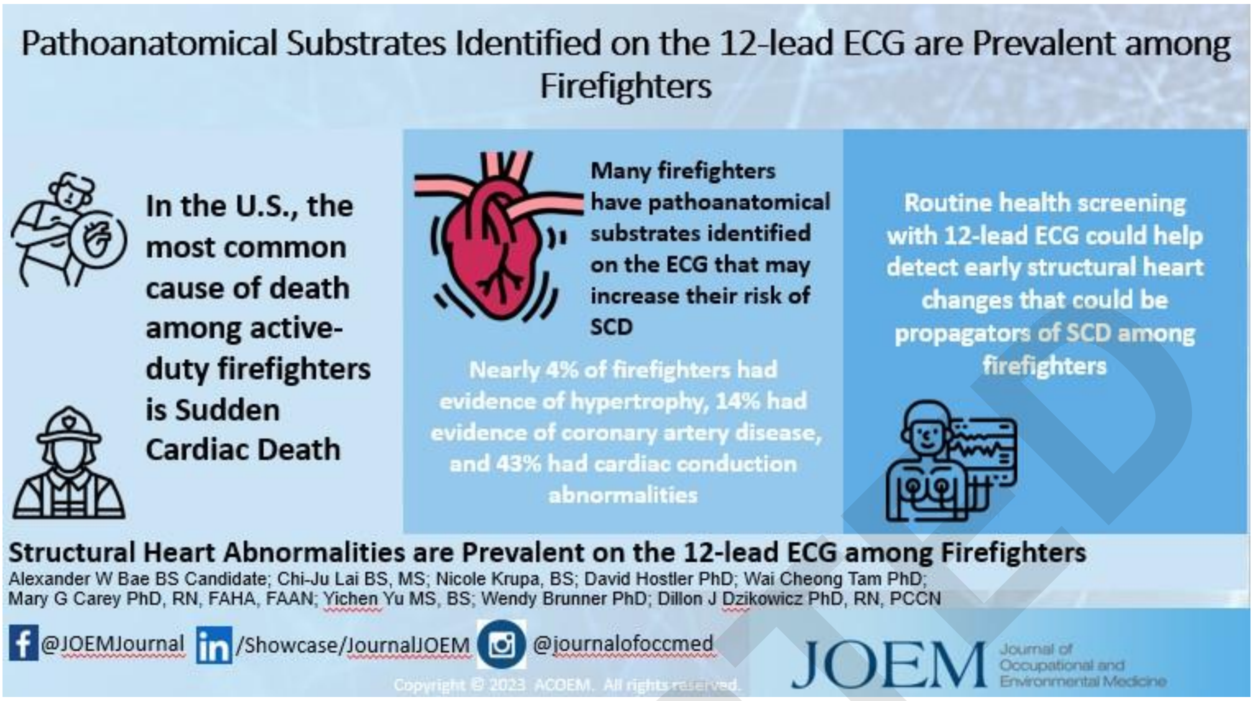
	Item No	Recommendation	Page No
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract (*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	1
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	4
Objectives	3	State specific objectives, including any prespecified hypotheses	4-5
Methods			
Study design	4	Present key elements of study design early in the paper	5-7
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	5-6
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up (*b*) For matched studies, give matching criteria and number of exposed and unexposed	5-7
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	5-7
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	5-6
Bias	9	Describe any efforts to address potential sources of bias	7
Study size	10	Explain how the study size was arrived at	7-8
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	8
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding (*b*) Describe any methods used to examine subgroups and interactions (*c*) Explain how missing data were addressed (*d*) If applicable, explain how loss to follow-up was addressed (*e*) Describe any sensitivity analyses	8
Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers	9

		potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed (b) Give reasons for non-participation at each stage (c) Consider use of a flow diagram	
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders (b) Indicate number of participants with missing data for each variable of interest (c) Summarise follow-up time (eg, average and total amount)	9
Outcome data	15*	Report numbers of outcome events or summary measures over time	10

Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included (*b*) Report category boundaries when continuous variables were categorized (*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	9-10
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	N/A
Discussion			
Key results	18	Summarise key results with reference to study objectives	11-12
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	12
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	12-13
Generalisability	21	Discuss the generalisability (external validity) of the study results	12-13
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	5

*Give information separately for exposed and unexposed groups.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at http://www.strobe-statement.org.


Pathoanatomical Substrates Identified on the 12-lead ECG are Prevalent among Firefighters
In the U.S., the most common cause of death among active-duty firefighters is Sudden Cardiac Death
Many firefighters have pathoanatomical substrates identified on the ECG that may increase their risk of SCD
Nearly 4% of firefighters had evidence of hypertrophy, 14% had evidence of coronary artery disease, and 43% had cardiac conduction abnormalities
Routine health screening with 12-lead ECG could help detect early structural heart changes that could be propagators of SCD among firefighters
Structural Heart Abnormalities are Prevalent on the 12-lead ECG among Firefighters
Alexander W Bae BS Candidate; Chi-Ju Lai BS, MS; Nicole Krupa, BS; David Hostler PhD; Wai Cheong Tam PhD;
Mary G Carey PhD, RN, FAHA, FAAN; Yichen Yu MS, BS; Wendy Brunner PhD; Dillon J Dzikowicz PhD, RN, PCCN
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