QTc Interval and Cardiac Risk: A Survey

www.surveyx.cn

Abstract

This survey explores the critical role of the QTc interval in electrocardiogram (ECG) diagnostics, emphasizing its significance in assessing cardiac risk and preventing sudden cardiac death. The QTc interval, a marker of cardiac electrical stability, is linked to increased susceptibility to ventricular arrhythmias and sudden cardiac events when prolonged. The survey systematically reviews the physiological basis of QTc, the mechanisms of QTc prolongation, and its association with mortality risks, highlighting the implications for clinical practice. Recent advancements in ECG technology, particularly the integration of machine learning and artificial intelligence, have significantly enhanced the detection and interpretation of QTc abnormalities. These technologies promise improved diagnostic accuracy and patient outcomes by facilitating early detection and timely intervention. The survey also discusses the transformative impact of wearable and mobile ECG technologies, which provide real-time, continuous cardiac monitoring, thereby increasing accessibility and convenience for patients. Furthermore, the survey identifies challenges in QTc interval research, such as data variability and noise, and underscores the need for robust analytical techniques and comprehensive datasets. The conclusion emphasizes the importance of ongoing research and technological innovation in ECG analysis to enhance the precision and reliability of QTc interval monitoring, ultimately contributing to better patient care and clinical outcomes.

1 Introduction

1.1 Structure of the Survey

This survey is structured into several key sections, each addressing critical aspects of QTc interval analysis and its implications for cardiac risk assessment. It begins with an introduction to the significance of the QTc interval in electrocardiogram (ECG) diagnostics, emphasizing its role in evaluating cardiac risk, arrhythmias, and sudden cardiac death. A background section follows, providing essential definitions and exploring the physiological basis of the QTc interval, which is fundamental for understanding its clinical relevance.

Subsequent sections investigate the correlation between QTc interval abnormalities and increased cardiac risk, examining mechanisms through which QTc prolongation can lead to arrhythmias and sudden cardiac death. This is complemented by a discussion on ECG as a diagnostic tool, highlighting advancements that improve the detection of QTc abnormalities [1].

The survey further analyzes the association between prolonged QTc intervals and mortality risks, detailing QTc's predictive value for sudden cardiac death and evaluating the influence of various medications on QTc intervals in critically ill patients. Insights into the prevalence of acquired long QT syndrome, associated risk factors, and systemic inflammation's role in QTc prolongation among COVID-19 patients are also discussed [2, 3, 4, 5, 6]. Additionally, current research is reviewed, focusing on innovative cardiac risk reduction strategies, the application of machine learning and artificial intelligence in QTc analysis, and the rise of wearable and mobile ECG technologies.

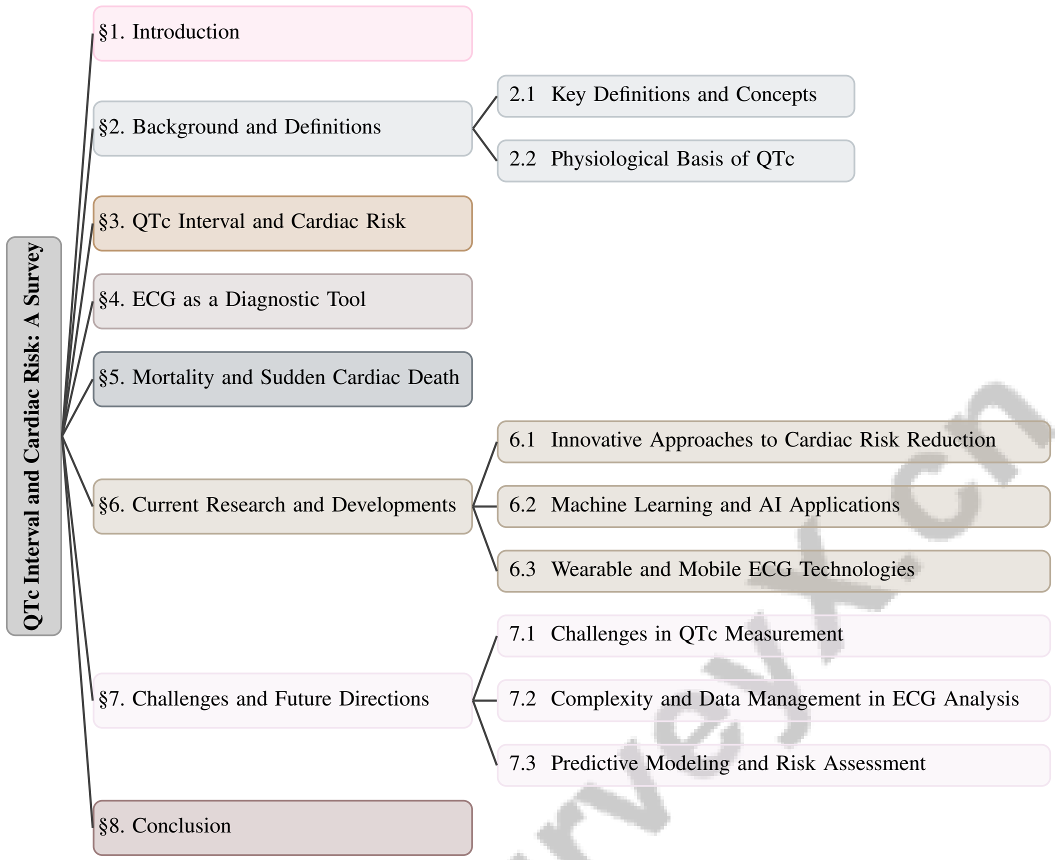

Figure 1: chapter structure

Finally, the survey addresses challenges in QTc interval research and ECG analysis, outlining potential future research directions and technological innovations that could enhance cardiac risk assessment. The conclusion synthesizes primary findings from recent advancements in ECG technology, highlighting the urgent need for ongoing research and innovation in cardiac health monitoring, particularly in automated diagnostics, deep learning applications for arrhythmia detection, and synthesizing 12-lead ECG from single-lead devices, all crucial for improving patient outcomes and addressing rare cardiac anomalies in clinical practice [7, 8, 9, 10].

1.2 Significance of QTc Interval in ECG Diagnostics

The QTc interval, which represents the corrected duration from the onset of the Q wave to the termination of the T wave in the cardiac electrical cycle, is a crucial marker of cardiac health in electrocardiogram (ECG) diagnostics. Prolongation of the QTc interval is strongly linked to increased risks of ventricular arrhythmias, such as torsades de pointes (TdP), and sudden cardiac death [11]. The ECG remains a vital non-invasive diagnostic tool, employing sophisticated physical principles to reveal critical cardiac insights that may be overlooked by conventional methods [12].

Accurate interpretation of the QTc interval is essential, as inaccuracies can lead to significant diagnostic errors, underscoring the need for advanced methodologies in ECG analysis [13]. This is particularly important in the context of psychiatric and other medications known to prolong the QTc interval, necessitating careful consideration of the balance between the risks of QTc prolongation and therapeutic benefits [11].

The relevance of QTc interval analysis is further emphasized in specific clinical scenarios, such as COVID-19 management, where treatments like hydroxychloroquine (HCQ) and azithromycin raise concerns about cardiotoxicity and QTc prolongation. The role of ECG data in enhancing COVID-19 diagnosis and mortality predictions is critical, highlighting its importance in clinical decision-making [14]. Additionally, monitoring QTc intervals in chronic kidney disease (CKD) patients is crucial due

AI-generated, for reference only.

to the heightened risk of fatal cardiac events linked to fluctuating potassium levels during dialysis [15].

Thus, the QTc interval is indispensable in ECG diagnostics, serving as both a predictive marker for cardiac risk and a guide for therapeutic decisions aimed at preventing adverse cardiac events. The advancement of innovative diagnostic techniques, such as self-supervised anomaly detection models, alongside the integration of cutting-edge technologies, is vital for improving the accuracy and reliability of QTc interval assessments across various clinical scenarios, including the detection of rare cardiac anomalies and evaluation of drug interactions affecting QTc prolongation. This comprehensive approach seeks to address existing gaps in ECG interpretation and enhance clinical decision-making [16, 8, 6, 3].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Key Definitions and Concepts

The QTc interval, a crucial metric in cardiac health evaluation, represents the heart rate-corrected QT interval, spanning from the onset of ventricular depolarization (Q wave) to the end of ventricular repolarization (T wave). This interval is pivotal for assessing cardiac function and detecting abnormalities, with significant implications in cardiac safety testing and drug approval processes [17, 18, 19]. It is particularly relevant for evaluating the risk of ventricular arrhythmias like torsades de pointes, with psychiatric medications and tyrosine kinase inhibitors (TKIs) being notable contributors to QTc prolongation and associated complications.

Electrocardiograms (ECGs) are essential for capturing the heart's electrical activity, where precise detection of P, QRS, and T wave boundaries is critical for accurate cardiac diagnosis [20]. However, ECG signal morphology can be affected by electrode displacement, leading to potential diagnostic errors due to variability in electrode positioning and patient anatomy [21]. The challenge of accurately estimating PR, QRS, and QT intervals from single lead-I ECG recordings highlights the traditional reliance on multiple leads for precision [22].

Key terms such as electrocardiography (ECG) and heart rate variability (HRV) indices are integral to cardiac monitoring, with HRV providing insights into autonomic regulation of heart rate [23]. The significance of ECG is underscored in contexts like pandemic health outcome predictions [14]. In chronic kidney disease (CKD), monitoring potassium levels is crucial due to their association with lethal cardiac events [15].

Enhancing cardiovascular diagnosis systems is critical for detecting heart conditions economically and accurately, especially for seniors in rural areas [24]. Encoding methods, such as slope and threshold value encoding, play a role in understanding ECG signal processing and cardiac health [25].

Understanding QTc intervals and ECG diagnostics is vital for advancing research and clinical practice. This knowledge supports the development of automated ECG interpretation systems, leveraging machine learning and large language models to enhance patient outcomes and risk assessments, particularly in evaluating drug interactions and diagnosing conditions like Short QT Syndrome. Such advancements enrich clinical decision-making and patient care [16, 3, 26, 6, 27].

2.2 Physiological Basis of QTc

The QTc interval, a critical measure in cardiac electrophysiology, reflects the time for ventricular depolarization and repolarization, essential for understanding electrical stability and arrhythmia susceptibility. QTc prolongation is associated with pathophysiological conditions like systemic inflammation, indicated by elevated C-Reactive Protein (CRP) levels, highlighting the importance of systemic factors in QTc evaluation [4].

Accurate QTc measurement requires heart rate corrections, such as the Fridericia formula, to ensure reliability across varying heart rates [28]. These corrections are crucial for reliable cardiac risk assessments. The QTc interval's physiological basis involves intricate cardiac electrical dynamics, significantly altered in arrhythmias, complicating P, QRS, and T wave delineation in ECG signals [29]. Current T-wave morphology assessment methods are inadequate, as limited measurements fail to capture the full complexity of T-wave changes [19].

The interaction between electrical and mechanical heart activities is crucial in QTc physiology, with distinct temporal relationships between electromechanical intervals during physical stress. Research shows that the QT interval responds to RR interval changes with a 10.5-second delay, while the systolic interval responds in 28.3 seconds. This interplay is vital for assessing cardiac function, drug interactions, and cardiovascular risks during treatments, such as those for COVID-19 [6, 30]. This interaction is particularly relevant during physical activities, where synchronization affects the QTc interval. Advanced analytical techniques are needed to interpret these complex dynamics, as ECG data non-stationarity presents challenges for consistent QTc measurement.

In cancer patients on tyrosine kinase inhibitors (TKIs), QTc prolongation is a recognized risk for serious cardiac events, including Torsade de Pointes (TdP) and sudden cardiac death (SCD) [31]. Monitoring QTc intervals in patients undergoing specific treatments is crucial, as acute and subacute cardiotoxicity are characterized by QTc prolongation and related measures [32].

A comprehensive understanding of QTc interval physiology enhances cardiac health assessments, improving diagnostic accuracy and clinical outcomes through tailored treatment strategies. This understanding is particularly pertinent given the impact of heart rate correction formulas on QTc stability and the need to address QT/RR hysteresis in drug-induced QTc studies, significantly influencing clinical decision-making and patient management [16, 2, 33, 3, 6]. Integrating innovative diagnostic techniques and considering systemic factors are essential for a comprehensive understanding of QTc dynamics and their implications for cardiac health.

In recent studies, the understanding of QTc interval prolongation and its associated arrhythmia risk has gained significant attention due to its clinical implications. To elucidate this complex relationship, Figure 2 provides a visual representation that illustrates the hierarchical structure of factors contributing to QTc interval prolongation. This figure highlights not only the underlying mechanisms and advancements in machine learning that aid in the assessment of these factors but also the challenges faced in monitoring QTc intervals. Furthermore, it delineates the relationship between QTc abnormalities and the development of arrhythmias, thereby enhancing our comprehension of this critical area in cardiac health. By integrating these insights, we can better appreciate the multifaceted nature of QTc interval prolongation and its implications for patient care.

3 QTc Interval and Cardiac Risk

3.1 Mechanisms of QTc Prolongation and Arrhythmias

QTc prolongation serves as a critical biomarker for cardiac electrical instability, heightening the risk of arrhythmias such as Torsades de Pointes (TdP) and sudden cardiac death. This condition arises from disruptions in ion channel function, myocardial tissue properties, and autonomic nervous system dynamics. Elevated C-Reactive Protein (CRP) levels, indicative of systemic inflammation, are linked to QTc prolongation and increased arrhythmogenic potential [4]. Electrolyte imbalances, particularly potassium fluctuations during dialysis, complicate electromechanical coupling and correlate with fatal cardiac events, highlighting the importance of monitoring potassium as a non-invasive cardiac risk indicator [15].

Figure 3 illustrates the mechanisms of QTc prolongation, emphasizing the interplay of biological factors, machine learning approaches, and clinical challenges. It highlights the critical role of ion channel function, CRP levels, and electrolyte imbalances as biological contributors to QTc prolongation. In the realm of machine learning, the figure underscores the significance of convolutional neural networks (CNNs), hybrid models, and transfer learning as innovative strategies for enhancing arrhythmia prediction. Additionally, it delineates the clinical challenges associated with drug safety, data scarcity, and monitoring issues that complicate patient management.

Advancements in machine learning have introduced adaptive algorithms that enhance QTc-related arrhythmia prediction accuracy. Deep learning, especially convolutional neural networks (CNNs), streamlines input data processing by emphasizing relevant features and minimizing noise from traditional ECG waveform analysis [34]. However, challenges persist due to the susceptibility of ECG signal characteristics to noise, which can impede accurate arrhythmia classification. Hybrid models integrating various machine learning methods have shown promise in improving classification accuracy by addressing these issues.

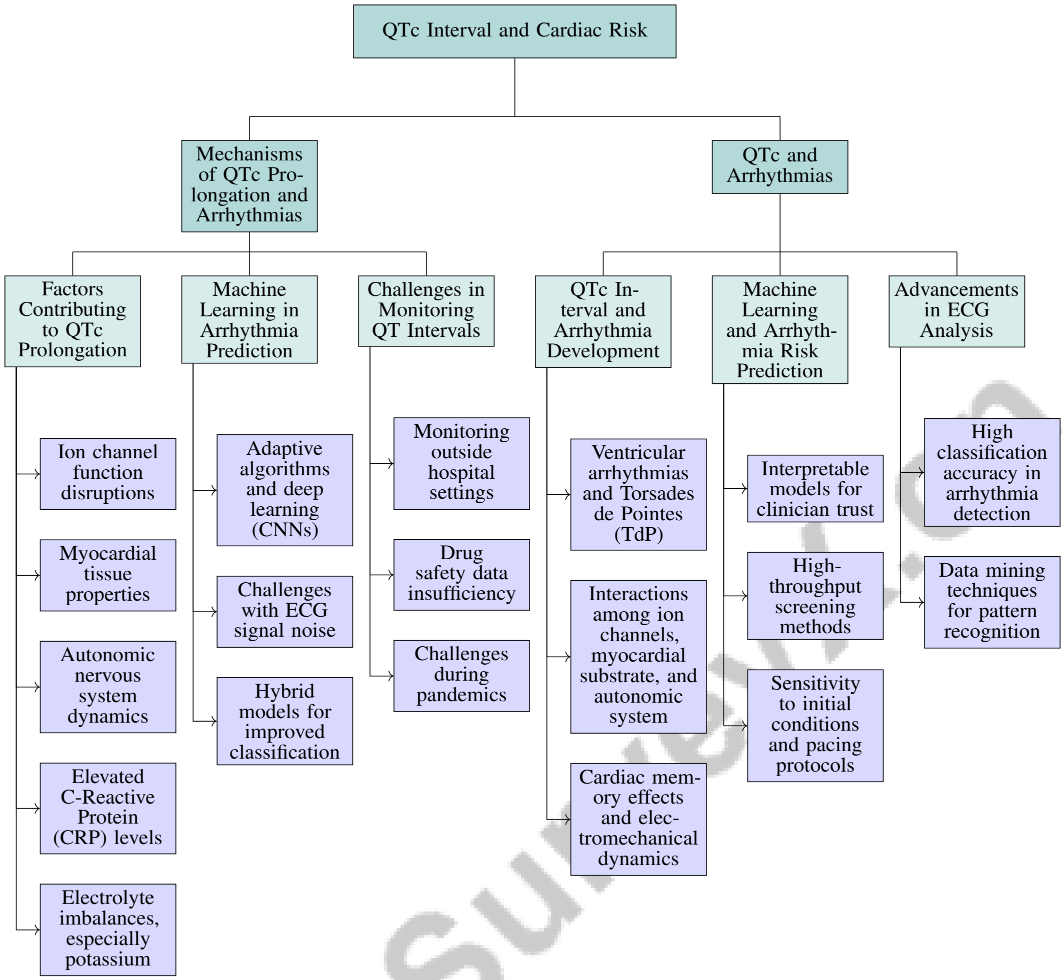

Figure 2: This figure illustrates the hierarchical structure of factors contributing to QTc interval prolongation and arrhythmia risk, highlighting mechanisms, machine learning advancements, and challenges in monitoring, as well as the relationship between QTc abnormalities and arrhythmia development.

Monitoring QT intervals in patients on antiarrhythmic medications outside hospital settings presents significant challenges, increasing healthcare costs and risks. This issue is exacerbated by insufficient data on drug safety in combination with comorbidities, especially in critically ill patients, which elevates arrhythmia risk. The scarcity of clinically annotated data during pandemics further complicates the identification of at-risk individuals, underscoring the need for robust data collection and analysis mechanisms [14].

A comprehensive understanding of the interactions between biological factors, such as inflammation indicated by elevated CRP levels, and systemic influences on QTc prolongation is essential for effective diagnostic and therapeutic strategies, particularly in the context of COVID-19 treatment, where these factors significantly affect patient outcomes [4, 6]. Continued research into innovative analytical techniques and machine learning applications is vital for enhancing the accuracy and reliability of QTc interval assessments in clinical practice.

3.2 QTc and Arrhythmias

The link between QTc interval abnormalities and arrhythmia development is a critical focus in cardiac electrophysiology. QTc prolongation is a recognized marker for increased susceptibility to ventricular arrhythmias, particularly Torsades de Pointes (TdP), which can lead to sudden cardiac death. This association is rooted in complex interactions among cardiac ion channel dysfunction, myocardial

AI-generated, for reference only.

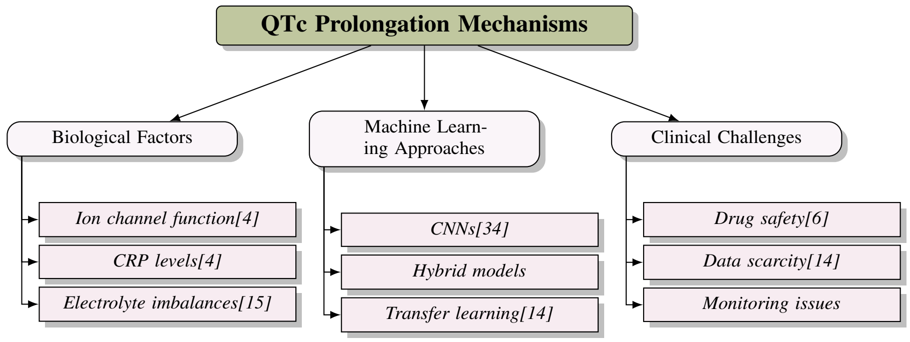

Figure 3: This figure illustrates the mechanisms of QTc prolongation, focusing on biological factors, machine learning approaches, and clinical challenges. It highlights the role of ion channel function, CRP levels, and electrolyte imbalances in biological factors. In machine learning, CNNs, hybrid models, and transfer learning are emphasized. Clinical challenges include drug safety, data scarcity, and monitoring issues.

substrate abnormalities, and autonomic nervous system imbalances, collectively influencing the heart's electromechanical dynamics. Temporal relationships observed in electromechanical intervals during physical stress tests reveal how variations in the RR interval can significantly affect QT, systolic, and diastolic intervals, highlighting the role of cardiac memory effects in heart function. The impact of these factors on ECG signal morphology necessitates comprehensive data collection and analysis, particularly in machine learning applications for ECG processing, where physiological variations can markedly alter heartbeat patterns [18, 30].

Recent advancements in machine learning have significantly improved the prediction of arrhythmogenic risk associated with QTc abnormalities. Interpretable machine learning models, as outlined by Verma et al., enhance transparency in prediction outcomes, fostering clinician trust and facilitating integration into routine clinical practice [35]. This contrasts with traditional black-box approaches that often lack the interpretability crucial for clinical decision-making. High-throughput screening methods, such as those described by Sun et al., demonstrate robust performance in identifying arrhythmia-related risk factors across diverse patient populations, achieving high area under the receiver operating characteristic (AUROC) values, with many International Classification of Diseases (ICD) codes exceeding 80

The complexity of arrhythmia development is further underscored by Zhao et al.'s findings on cardiac alternans, which indicate multiple alternans solutions in cardiac fibers sensitive to initial conditions and pacing protocols [36]. This sensitivity highlights the necessity for personalized approaches in managing arrhythmogenic risk. Automated ECG analysis has also advanced significantly, with methods achieving high classification accuracy across multiple arrhythmia types. Bazarghan et al. reported a classification accuracy of 99.42

Additionally, data mining techniques, as surveyed by Tyagi et al., play a crucial role in identifying patterns and risk factors associated with ECG data. By clustering similar ECG data points, these techniques enhance the predictive capabilities of ECG analysis systems, facilitating the recognition of arrhythmogenic patterns [37].

4 ECG as a Diagnostic Tool

The electrocardiogram (ECG) remains indispensable in cardiac diagnostics, offering critical insights into cardiac health through technological advancements that enhance its diagnostic utility. This section delves into the ECG's role in cardiac monitoring and diagnosis, highlighting its applications and the essential information it provides on cardiac function and abnormalities.

4.1 Role of ECG in Cardiac Monitoring and Diagnosis

ECG is a fundamental tool in cardiac monitoring and diagnosis, providing a non-invasive, efficient method to detect cardiac abnormalities such as QTc prolongation, which can signal severe conditions like arrhythmias and sudden cardiac death [23, 14]. By capturing the heart's electrical activity, ECG aids in the early detection and management of cardiac disorders.

Advancements in automated ECG analysis have enhanced the detection of cardiac abnormalities, enabling timely clinical interventions. For instance, Zhu et al. demonstrated ECG signal reconstruction from photoplethysmogram (PPG) data, offering a low-cost, continuous monitoring solution with high accuracy, thereby expanding access to cardiac diagnostics [38]. This is particularly advantageous in settings where traditional ECG setups are impractical.

The integration of Internet of Things (IoT) technologies with ECG systems has further advanced cardiac monitoring, allowing continuous remote surveillance of patients' cardiac health. This approach is especially beneficial for individuals in remote or underserved areas, enhancing healthcare accessibility and providing critical diagnostic capabilities [39]. Innovations in ECG monitoring are crucial in managing conditions like chronic kidney disease (CKD), where continuous monitoring aids in reconstructing potassium concentrations, preventing lethal cardiac events linked to electrolyte imbalances [15].

Moreover, the ECG's diagnostic utility is enhanced by methodologies like ECG-PPG Correlation Analysis, which records and analyzes ECG and PPG signals to identify correlations [40]. This comprehensive approach provides a holistic view of a patient's cardiovascular status, bolstering the ECG's role in health monitoring.

4.2 Technological Advancements in ECG Analysis

Recent advancements in ECG analysis have significantly improved the detection and interpretation of QTc intervals, aiding in the diagnosis and management of cardiac conditions. Machine learning techniques, such as QTNet—a multi-task regression Convolutional Neural Network model—facilitate continuous monitoring of QT intervals from Lead-I ECG signals, essential for timely interventions in outpatient settings [22].

Deep learning approaches, including transforming 1D ECG signals into a 2D feature space via the Wigner-Ville distribution and employing deep convolutional neural networks (CNNs) for classification, have further refined ECG analysis accuracy [41]. These methods leverage rich feature sets extracted from ECG signals for precise detection of QTc prolongations and other cardiac abnormalities.

Secondary wavelets tailored to QRS complex characteristics represent a significant improvement over methodologies relying solely on primary wavelets, enhancing QRS complex detection precision critical for accurate QT interval measurement [42].

The SIM-ECG system, which utilizes signal importance mask feedback from expert ECG readers, has improved classification accuracy and interpretability in ECG analysis [43]. This system integrates expert insights into the machine learning process, enhancing ECG diagnostic reliability.

Hybrid approaches combining RR interval features with frequency domain features from Fast Fourier Transform (FFT) have advanced ECG signal classification [44]. These models provide comprehensive ECG data analyses, improving QTc interval abnormality detection.

Data mining techniques, including classification, clustering, and prediction, have been applied to ECG data, enhancing cardiac risk factor detection [37]. These techniques identify patterns and trends in ECG signals, contributing to more accurate risk assessments.

Wearable ECG devices have advanced significantly, recognized for their role in continuous monitoring and disease detection [45]. Combined with advanced analytical methods, these devices offer versatile tools for predictive analytics, adapting to various data types and providing critical insights into cardiac health.

As illustrated in Figure 4, the hierarchical categorization of technological advancements in ECG analysis highlights key machine learning techniques, hybrid and feedback systems, and wearable ECG devices. Each category encompasses specific methods and technologies that contribute to improved ECG diagnostic accuracy and reliability.

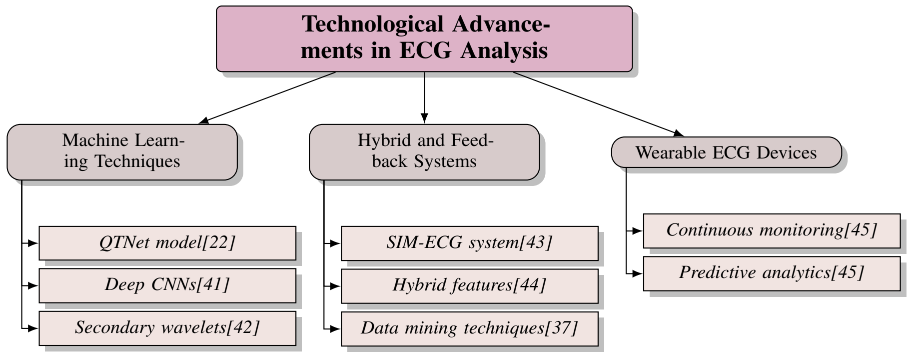

Figure 4: This figure illustrates the hierarchical categorization of technological advancements in ECG analysis, highlighting key machine learning techniques, hybrid and feedback systems, and wearable ECG devices. Each category includes specific methods and technologies contributing to improved ECG diagnostic accuracy and reliability.

4.3 Diagnostic Advancements in ECG Analysis

Recent diagnostic advancements in ECG analysis have greatly enhanced the detection and interpretation of QTc abnormalities, improving clinical outcomes in cardiac care. Deep learning methods have been transformative, outperforming traditional techniques in disease detection and classification tasks. For example, the model developed by Joung et al. achieved F1-scores exceeding 99

Wavelet transforms effectively capture localized ECG signal features, facilitating accurate classification of various myocardial infarction types, as demonstrated by Banerjee et al. [46]. This method enhances myocardial infarction detection precision by correlating wavelet-transformed features with specific cardiac events.

Advanced image processing techniques have contributed to diagnostic improvements. The method by Pazos-Santomé et al. converts printed ECGs into digital signals, enhancing QTc abnormality detection and interpretation [47]. This innovation facilitates the transition from traditional paper-based ECGs to digital analysis, improving accessibility and diagnostic efficiency.

Uncertainty quantification methods, using conditional diffusion processes to generate multiple ECG samples from PPG signals, enhance cardiovascular assessments by quantifying uncertainty in ECG analysis [48]. This capability is crucial for ensuring consistent and accurate ECG interpretations across diverse clinical scenarios.

Comparative analysis by Zappon et al. indicates that while various uncertainties impact ECG morphology, essential diagnostic features remain largely intact across different studies and methods [49]. This finding underscores the robustness of current ECG analysis techniques in maintaining diagnostic integrity despite inherent variabilities.

Furthermore, the method by Mousavi et al. demonstrates superior performance in classifying ECG heartbeats compared to existing algorithms, effectively addressing challenges of class imbalance and evaluation bias [50]. This improvement in classification accuracy is vital for the reliable detection of arrhythmias and other cardiac abnormalities.

5 Mortality and Sudden Cardiac Death

5.1 QTc Prolongation and Mortality Risks

QTc prolongation is a significant indicator of increased mortality risk, particularly in individuals with Long QT Syndrome (LQTS), which predisposes them to life-threatening ventricular arrhythmias and sudden cardiac death. This risk is heightened in patients with comorbidities like chronic kidney disease (CKD), where monitoring potassium levels is crucial to prevent fatal outcomes [15]. Identifying medications that prolong the QTc interval is vital for patient safety, with research delineating specific drugs and guidelines to mitigate these risks [11]. For example, QTc prolongation and elevated troponin levels are common in patients undergoing ACT chemotherapy for breast cancer, necessitating rigorous cardiac monitoring [32].

The predictive value of QTc interval prolongation is also evident in COVID-19 patients, where prolonged intervals correlate with increased mortality due to myocardial inflammation [4]. This highlights the importance of integrating QTc monitoring into COVID-19 management strategies to enhance clinical outcomes. Wearable ECG devices have proven effective for early arrhythmia detection, offering non-inferior diagnostic speed and improved patient outcomes compared to traditional methods [51]. These devices facilitate continuous monitoring, enabling timely interventions that can reduce mortality risks associated with prolonged QTc intervals.

As illustrated in Figure 5, the primary categories of QTc prolongation risks, the impact of COVID-19 on QTc intervals, and technological advancements in ECG analysis are depicted. Each category highlights specific factors or innovations related to QTc interval monitoring and management. Machine learning models, particularly those using Convolutional Recurrent Neural Network (CRNN) architectures, have significantly enhanced ECG analysis accuracy. These models achieve high classification rates for various arrhythmias with fewer input features, improving risk assessments [52, 53].

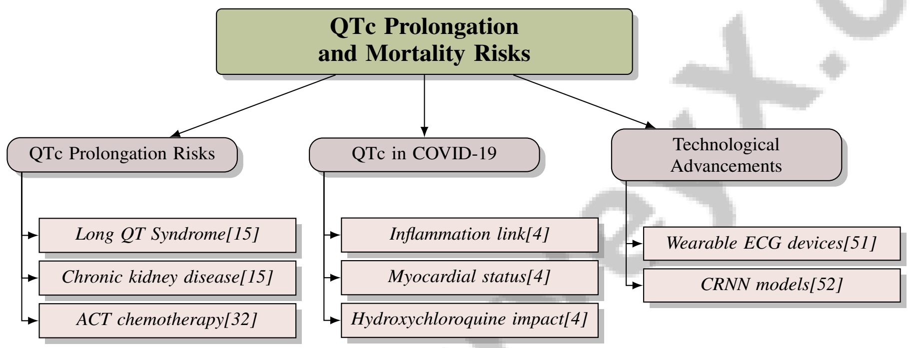

Figure 5: This figure illustrates the primary categories of QTc prolongation risks, the impact of COVID-19 on QTc intervals, and technological advancements in ECG analysis. Each category highlights specific factors or innovations related to QTc interval monitoring and management.

5.2 Predictive Role of QTc in Sudden Cardiac Death

The QTc interval is a crucial predictive marker for sudden cardiac death (SCD), reflecting the heart's electrical stability and arrhythmogenic risk. QTc prolongation is strongly associated with an increased likelihood of ventricular arrhythmias, such as Torsades de Pointes, which can lead to SCD. In cancer patients treated with tyrosine kinase inhibitors (TKIs), incidents of QTc prolongation underscore the necessity of routine ECG monitoring to avert serious cardiac events [31].

During acute health crises like the COVID-19 pandemic, the QTc interval has proven valuable for assessing mortality risks. Pre-trained models on historical ECG data have significantly enhanced prediction accuracy for COVID-19 mortality, demonstrating ECG's utility in urgent health scenarios [14]. This approach refines mortality risk assessments, facilitating timely clinical decision-making.

Beyond traditional cardiovascular contexts, the QTc interval provides insights into systemic health challenges. Advanced analytical techniques and continuous monitoring technologies enable clinicians to proactively manage risks associated with QTc prolongation, reducing SCD incidence and improving patient outcomes across clinical settings through automated ECG interpretation and enhanced diagnostic accuracy [54, 26].

5.3 Impact of Medications on QTc and Mortality

The influence of medications on QTc intervals and their potential impact on mortality risks is a critical research area in cardiology. Drugs like hydroxychloroquine and azithromycin, extensively used during the COVID-19 pandemic, pose significant QTc prolongation risks, necessitating careful monitoring to mitigate adverse cardiac outcomes [6]. Recent advancements in ECG analysis have improved QTc abnormality detection and interpretation, influencing mortality risk assessments. AI-driven platforms like QTNet enable continuous QT interval monitoring, reducing inpatient care needs and facilitating timely interventions for patients on antiarrhythmic therapy [55].

Integrating Internet of Things (IoT) technologies into ECG monitoring systems enhances diagnostic accuracy and reduces healthcare costs, particularly benefiting rural populations [24]. These systems facilitate early detection of medication-induced QTc prolongation and subsequent cardiac events. However, limitations in ECG-AI application accuracy highlight the need for larger, curated datasets for validation [56]. Future research should focus on assessing drug-induced changes in T-wave morphology, which may also influence mortality risks [19]. Recommendations emphasize improving data collection methodologies and exploring innovative model architectures to enhance ECG abnormality detection and interpretation [57].

6 Current Research and Developments

6.1 Innovative Approaches to Cardiac Risk Reduction

Recent advancements in electrocardiogram (ECG) analysis have introduced innovative strategies to mitigate cardiac risks linked to QTc interval abnormalities. Leveraging machine learning, large language models, and self-supervised learning, these strategies enhance ECG diagnostic accuracy and patient outcomes, especially in underdeveloped regions with limited healthcare access. Automated ECG interpretation, retrieval-augmented report generation, and anomaly detection streamline clinical workflows, ensuring timely and precise diagnoses for improved clinical decision-making [58, 26, 59, 8, 27]. Machine learning and deep learning techniques, including transfer learning, have been instrumental in cardiac risk assessment, notably during pandemics like COVID-19, where systemic inflammation impacts QTc intervals.

Adaptive algorithms enhance ECG classifiers using comprehensive datasets such as LUDB, improving ECG signal delineation through multi-lead recordings essential for accurate QTc interval assessment [20]. Uncertainty quantification (UQ) methods improve model reliability and interpretability, providing clinicians clearer insights into prediction uncertainties [48].

Integrating Internet of Things (IoT) technology with ECG monitoring systems enables real-time data collection and analysis, enhancing cardiovascular health monitoring accuracy and accessibility [24]. This advancement addresses cardiac signal variability and improves ECG model generalizability across diverse populations.

Frameworks like QTNet estimate QT intervals from single-lead ECGs, facilitating continuous monitoring and QT prolongation detection in outpatient settings [55]. This reduces inpatient care needs, allowing timely interventions and improved patient management.

Adaptive neuro-fuzzy inference systems (ANFIS) in ECG analysis merge fuzzy systems' interpretability with neural networks' accuracy, focusing on ECG features for potassium estimation. This approach is vital for non-invasive monitoring of electrolyte imbalances linked to cardiac risks [39].

Future research should focus on developing personalized monitoring systems, enhancing robotic-assisted healthcare, and integrating intelligent features into ECG monitoring systems to improve adaptability and effectiveness [60]. Advanced data augmentation techniques and model flexibility to accommodate overlapping waveforms can further enhance performance across a broader range of arrhythmias.

6.2 Machine Learning and AI Applications

The integration of machine learning (ML) and artificial intelligence (AI) into ECG analysis has significantly advanced QTc interval and cardiac risk assessment. Developments in data mining techniques have improved ECG data analysis accuracy and efficiency, facilitating critical arrhythmia identification and enhancing predictive capabilities. Hybrid models combining time-domain and frequency-domain features improve ECG classification accuracy, distinguishing these methods from traditional approaches [44].

Non-linear modeling techniques in ML frameworks enhance prediction accuracy. Innovative methodologies, like colorimetry-based grid removal in ECG analysis, outperform grayscale techniques, emphasizing advanced feature extraction methods' importance in ECG signal analysis [47].

Deep learning (DL) plays a pivotal role in ECG analysis. Convolutional neural network (CNN) models exhibit superior ECG classification performance, achieving high accuracy and robustness in detecting various arrhythmias [41]. Diverse training data improves ECG delineation, as evidenced by extensive internal databases of recordings from patients with various arrhythmias [29].

Synthesizing missing ECG leads' morphology and timing based on historical data enhances ECG analysis, utilizing shared representation spaces for better feature extraction and integration [61].

AI-driven platforms monitor electrolyte imbalances, such as potassium levels, critical for cardiac risk assessment [39]. IoT technologies in ECG monitoring systems enhance cardiovascular health monitoring through real-time data collection and analysis capabilities [60].

6.3 Wearable and Mobile ECG Technologies

Wearable and mobile ECG technologies have transformed cardiac health assessment, especially in monitoring QTc intervals. Devices like the Apple Watch, Fitbit, and ZioPatch enable real-time, continuous cardiac monitoring, enhancing patient accessibility and convenience [57]. These technologies allow ECG signal acquisition without professional assistance, making cardiac diagnostics more widely accessible [7].

As illustrated in Figure 6, the figure highlights the key components and innovations in wearable and mobile ECG technologies, showcasing devices that enhance accessibility, advanced computational models for diagnostics, and innovative solutions that improve ECG data collection and processing.

Advanced computational models, including machine learning and deep learning, integrated into wearable ECG systems, enhance diagnostic capabilities. QTNet effectively identifies drug-induced QT prolongation, facilitating outpatient monitoring and care using wearable ECG devices [55]. These technologies enable automatic feature extraction, improving QTc abnormality detection accuracy and supporting healthcare professionals in clinical decision-making [62].

Innovative solutions like ArdMob-ECG provide low-cost, user-friendly data collection alternatives, particularly beneficial in remote areas and during health crises like COVID-19 [63]. Synthesizing accurate 12-lead ECGs from affordable single-lead devices significantly enhances cardiac diagnostics accessibility [10].

Adapted wavelets in ECG signal processing improve R peak detection accuracy amidst noise and artifacts, highlighting clinical applications' potential in wearable devices [42]. Techniques like CNNef demonstrate superior performance in wearable applications, achieving high accuracy and noise immunity [44].

Cloud and edge computing methodologies enhance wearable ECG technologies' capabilities by decoupling computing power from portable devices' limitations, facilitating efficient data processing and scalable cardiac health monitoring solutions [64]. Future research should focus on developing cloud-based systems connected to wearable devices for real-time ECG monitoring, utilizing advanced deep learning techniques to further enhance their utility [57].

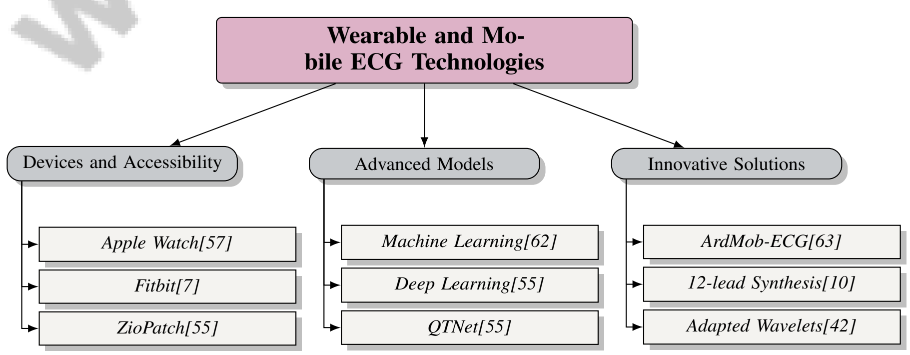

Figure 6: This figure illustrates the key components and innovations in wearable and mobile ECG technologies, highlighting devices that enhance accessibility, advanced computational models for diagnostics, and innovative solutions improving ECG data collection and processing.

7 Challenges and Future Directions

The accurate assessment of the QTc interval is a cornerstone in cardiac health, serving as a crucial marker for arrhythmias and cardiovascular issues. This section examines the complexities involved in QTc measurement, highlighting the factors that complicate this process and their implications for clinical practice and research. The following subsections will explore the intricacies and obstacles encountered in QTc measurement, establishing a foundation for further exploration of this critical aspect of cardiac monitoring.

7.1 Challenges in QTc Measurement

QTc interval measurement is fraught with challenges impacting both clinical practice and research. The inherent variability of ECG signals complicates arrhythmia detection across diverse populations [41], exacerbated by dependence on historical data and precision in fiducial point detection, leading to potential errors in real-time applications [10]. The absence of a comprehensive framework for ECG system design and analysis contributes to inefficiencies [60].

Noise and artifacts in ECG signals hinder accurate R-peak identification, crucial for QTc measurement. Manual classification of ECG beats is labor-intensive and error-prone, especially when distinguishing similar arrhythmia types. Current methods often lack formal validation and analytical techniques to establish relationships between ECG and other biosignals like PPG [40]. Dependence on high-quality PPG data for signal reconstruction introduces potential inaccuracies in signal alignment [38].

The limited generalizability of findings due to reliance on specific datasets that may not encompass comprehensive ECG time series data poses another significant challenge [39]. This limitation is compounded by the retrospective nature of many studies, necessitating larger sample sizes for validation [4]. The variability in ECG signals and the challenge of achieving high accuracy across multiple arrhythmia types continue to obstruct effective ECG analysis [41].

Integrating machine learning and AI into ECG analysis introduces additional challenges, particularly the lack of comprehensive evaluations of uncertainty quantification (UQ) methods across diverse datasets and clinical scenarios, which may lead to overfitting [65]. Furthermore, limited clinician feedback in some methods restricts their potential for improvement [43].

Addressing these challenges requires robust algorithms capable of managing ECG signal variability and integrating multiple biosignals for comprehensive analysis. Enhancing data quality, standardization, model interpretability, and expanding dataset scopes are essential for more accurate QTc interval measurements. The parallels between challenges in QTc measurement and those in predicting COVID-19 outcomes due to limited clinical data during pandemics underscore the need for ongoing research and innovation [14]. The reliance on synthetic PPG signals raises questions about the generalizability of results to real-world scenarios, necessitating further validation [48].

Figure 7 illustrates the primary challenges in QTc measurement, categorized into ECG signal variability, noise and artifacts, and machine learning challenges. Each category is supported by specific issues and references to relevant studies, providing a visual representation that complements the discussion of these multifaceted challenges.

7.2 Complexity and Data Management in ECG Analysis

The complexities of ECG data management and analysis significantly influence QTc research, presenting challenges that must be addressed to enhance diagnostic accuracy and clinical outcomes. Network latency and fault tolerance can affect the consistency and performance of ECG monitoring systems, particularly in real-time applications [66]. These issues are compounded by the need for robust data management frameworks capable of efficiently handling large volumes of ECG data.

The reliance on high-quality annotated datasets is critical for effective ECG analysis. The black-box nature of deep learning models, coupled with interpretability challenges, limits their clinical application [67]. This lack of transparency can hinder the adoption of advanced analytical techniques, as clinicians may be reluctant to trust models that do not provide clear insights into their decision-making processes.

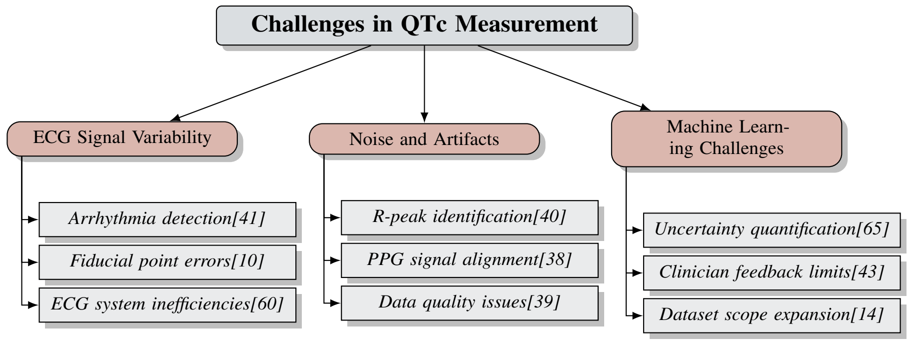

Figure 7: This figure illustrates the primary challenges in QTc measurement, categorized into ECG signal variability, noise and artifacts, and machine learning challenges. Each category is supported by specific issues and references to relevant studies.

Standardization in testing and annotations remains a persistent issue, with many studies lacking clinical validation, leading to inconsistencies in ECG data interpretation [68]. This challenge is exacerbated by the necessity to train separate models for each disorder, as seen in query-based ECG classification methods, which do not enhance classifier architecture [69].

The variability in ECG signals, along with unanswered questions regarding the identification of model parameters for optimal calibration of cardiac digital twins (CDTs) to ECGs, underscores the need for more precise and adaptable analytical techniques [49]. Future research should focus on improving the robustness of ECG analysis methods against noise and artifacts, exploring their application across diverse populations and conditions to ensure broader applicability and reliability [38].

7.3 Predictive Modeling and Risk Assessment

The future of predictive modeling and risk assessment for QTc-related cardiac risk hinges on optimizing computational efficiency and enhancing model robustness against noise, thereby improving reliability in diverse clinical settings. Optimizing algorithms used in ECG monitoring devices could significantly enhance their applicability across various healthcare domains [45]. Emphasizing the classification of minority classes and incorporating data from multiple ECG leads are critical for improving model performance and ensuring comprehensive risk assessments [70].

Developing standardized protocols for implementing uncertainty quantification (UQ) in clinical biosignal analysis is essential for enhancing model reliability. Future research should explore novel UQ methods and assess their effectiveness in real-world medical applications, thereby improving the interpretability and trustworthiness of predictive models [65]. Expanding datasets to include diverse populations and optimizing models for real-time applications are crucial for integrating these models into existing healthcare systems, ensuring broader applicability and utility [41].

Addressing unanswered questions in ECG monitoring systems, such as defining a complete lifecycle and integrating emerging technologies like AI and IoT, will be pivotal in advancing predictive modeling frameworks [60]. These efforts will facilitate the development of more adaptable and efficient systems capable of delivering accurate and timely cardiac risk assessments.

8 Conclusion

The survey underscores the pivotal role of QTc interval monitoring in minimizing cardiac risk and preventing sudden cardiac death, highlighting its critical importance in clinical diagnostics and patient management. As a key indicator of cardiac electrical stability, the QTc interval's prolongation signals an increased risk of ventricular arrhythmias and sudden cardiac events. The integration of advanced technologies such as machine learning and AI into ECG analysis has significantly enhanced the detection and interpretation of QTc abnormalities, facilitating improved diagnostic precision and patient outcomes.

The evolution of wearable and mobile ECG technologies has revolutionized cardiac monitoring, offering real-time, continuous assessments that enhance patient accessibility and convenience. These advancements are crucial for the early detection and intervention necessary to reduce mortality risks associated with QTc prolongation.

In addition, innovative analytical approaches, including statistical indices for differentiating between normal sinus rhythm and ventricular arrhythmias, emphasize the need for ongoing research and innovation in ECG analysis. The continuous exploration and adoption of emerging technologies are vital for advancing our understanding of QTc dynamics and refining cardiac risk assessment methodologies.

AI-generated, for reference only.

References

[1] Sourav Chowdhury, Apratim Ghosal, Suparna Roychowhury, and Indranath Chaudhuri. Studying ecg signals using nonlinear oscillators and genetic algorithm, 2024.

[2] Marek Malik, Christine Garnett, Katerina Hnatkova, Lars Johannesen, Jose Vicente, and Norman Stockbridge. Importance of qt/rr hysteresis correction in studies of drug-induced qtc interval changes. *Journal of pharmacokinetics and pharmacodynamics*, 45:491–503, 2018.

[3] Rui Providência, Nabeela Karim, Neil Srinivasan, Shohreh Honarbakhsh, Maria João Vidigal Ferreira, Lino Gonçalves, Eloi Marijon, and Pier D Lambiase. Impact of qtc formulae in the prevalence of short corrected qt interval and impact on probability and diagnosis of short qt syndrome. *Heart*, 104(6):502–508, 2018.

[4] Simone Gulletta, Paolo Della Bella, Luigi Pannone, Giulio Falasconi, Lorenzo Cianfanelli, Savino Altizio, Elena Cinel, Valentina Da Prat, Antonio Napolano, Giuseppe D'Angelo, et al. Qtc interval prolongation, inflammation, and mortality in patients with covid-19. *Journal of Interventional Cardiac Electrophysiology*, pages 1–8, 2022.

[5] Flávia Medeiros Fernandes, Eliane Pereira Silva, Rand Randall Martins, and Antonio Gouveia Oliveira. Qtc interval prolongation in critically ill patients: Prevalence, risk factors and associated medications. *PLoS One*, 13(6):e0199028, 2018.

[6] Dan M Roden, Robert A Harrington, Athena Poppas, and Andrea M Russo. Considerations for drug interactions on qtc interval in exploratory covid-19 treatment. *Journal of the American College of Cardiology*, 75(20):2623, 2020.

[7] Neha Arora and Biswajit Mishra. Origins of ecg and evolution of automated dsp techniques: A review, 2021.

[8] Aofan Jiang, Chaoqin Huang, Qing Cao, Yuchen Xu, Zi Zeng, Kang Chen, Ya Zhang, and Yanfeng Wang. Self-supervised anomaly detection pretraining enhances long-tail ecg diagnosis, 2024.

[9] Praveen Kumar Pandian Shanmuganathan and Vatsal Sivaratri. Integrating deep learning for arrhythmia detection with automated drug delivery: A comprehensive approach to cardiac health monitoring and treatment, 2024.

[10] Kahkashan Afrin, Parikshit Verma, Sanjay S. Srivatsa, and Satish T. S. Bukkapatnam. Simultaneous 12-lead electrocardiogram synthesis using a single-lead ecg signal: Application to handheld ecg devices, 2018.

[11] Glen L Xiong, Aaron Pinkhasov, Jed P Mangal, Heather Huang, Jeffrey Rado, Jane Gagliardi, Dustin Demoss, David Karol, Shannon Suo, Michael Lang, et al. Qtc monitoring in adults with medical and psychiatric comorbidities: Expert consensus from the association of medicine and psychiatry. *Journal of Psychosomatic Research*, 135:110138, 2020.

[12] Rafael M. Gutiérrez and Luis A. Sandoval. Detecting stochastic information of electrocardiograms, 2003.

[13] Yiannis Contoyiannis, Fotis Diakonos, and Myron Kampitakis. Applying the method of critical fluctuations on human electrocardiograms, 2019.

[14] Weijie Sun, Sunil Vasu Kalmady, Nariman Sepehrvand, Luan Manh Chu, Zihan Wang, Amir Salimi, Abram Hindle, Russell Greiner, and Padma Kaul. Improving ecg-based covid-19 diagnosis and mortality predictions using pre-pandemic medical records at population-scale, 2023.

[15] Nicolas Pilia, Cristiana Corsi, Stefano Severi, Olaf Dössel, and Axel Loewe. Reconstruction of potassium concentrations with the ecg on imbalanced datasets, 2020.

[16] Jungwoo Oh, Gyubok Lee, Seongsu Bae, Joon myoung Kwon, and Edward Choi. Ecg-qa: A comprehensive question answering dataset combined with electrocardiogram, 2023.

[17] Selcan Kaplan Berkaya, Alper Kursat Uysal, Efnan Sora Gunal, Semih Ergin, Serkan Gunal, and M Bilginer Gulmezoglu. A survey on ecg analysis. *Biomedical Signal Processing and Control*, 43:216–235, 2018.

[18] Marat Bogdanov, Salim Baigildin, Aygul Fabarisova, Konstantin Ushenin, and Olga Solovyova. Effects of lead position, cardiac rhythm variation and drug-induced qt prolongation on performance of machine learning methods for ecg processing, 2020.

[19] Yingchun Zhou and Nell Sedransk. Functional data analytic approach of modeling ecg t-wave shape to measure cardiovascular behavior, 2010.

[20] Alena I. Kalyakulina, Igor I. Yusipov, Victor A. Moskalenko, Alexander V. Nikolskiy, Konstantin A. Kosonogov, Grigory V. Osipov, Nikolai Yu. Zolotykh, and Mikhail V. Ivanchenko. Ludb: a new open-access validation tool for electrocardiogram delineation algorithms, 2020.

[21] Andra Oltmann, Roman Kusche, and Philipp Rostalski. Spatial sensitivity of ecg electrode placement, 2021.

[22] Ridwan Alam and Collin Stultz. Estimating ecg intervals from lead-i alone: External validation of supervised models, 2024.

[23] Kavya Remesh and Job Chunkath. Comparison of hrv indices of ecg and bcg signals, 2023.

[24] Md. Obaidur Rahman, Mohammod Abul Kashem, Al-Akhir Nayan, Most. Fahmida Akter, Fazly Rabbi, Marzia Ahmed, and Mohammad Asaduzzaman. Internet of things (iot) based ecg system for rural health care, 2022.

[25] Luis A. Mora and Jhon E. Amaya. Effect of encoding method on the distribution of cardiac arrhythmias, 2011.

[26] Jielin Qiu, Jiacheng Zhu, Shiqi Liu, William Han, Jingqi Zhang, Chaojing Duan, Michael Rosenberg, Emerson Liu, Douglas Weber, and Ding Zhao. Automated cardiovascular record retrieval by multimodal learning between electrocardiogram and clinical report, 2023.

[27] Jialu Tang, Tong Xia, Yuan Lu, Cecilia Mascolo, and Aaqib Saeed. Electrocardiogram report generation and question answering via retrieval-augmented self-supervised modeling, 2024.

[28] Irena Andršová, Katerina Hnatkova, Kateřina Helánová, Martina Šišáková, Tomáš Novotnỳ, Petr Kala, and Marek Malik. Problems with bazett qtc correction in paediatric screening of prolonged qtc interval. *BMC pediatrics*, 20:1–10, 2020.

[29] Chankyu Joung, Mijin Kim, Taejin Paik, Seong-Ho Kong, Seung-Young Oh, Won Kyeong Jeon, Jae hu Jeon, Joong-Sik Hong, Wan-Joong Kim, Woong Kook, Myung-Jin Cha, and Otto van Koert. Deep learning based ecg segmentation for delineation of diverse arrhythmias, 2024.

[30] Sajjad Karimi, Shirin Karimi, Amit J. Shah, Gari D. Clifford, and Reza Sameni. Electromechanical dynamics of the heart: A study of cardiac hysteresis during physical stress test, 2024.

[31] Anan A Abu Rmilah, Grace Lin, Kebede H Begna, Paul A Friedman, and Joerg Herrmann. Risk of qtc prolongation among cancer patients treated with tyrosine kinase inhibitors. *International journal of cancer*, 147(11):3160–3167, 2020.

[32] Pedro Veronese, Denise Tessariol Hachul, Mauricio Ibrahim Scanavacca, Ludhmila Abrahão Hajjar, Tan Chen Wu, Luciana Sacilotto, Carolina Veronese, and Francisco Carlos da Costa Darrieux. Effects of anthracycline, cyclophosphamide and taxane chemotherapy on qtc measurements in patients with breast cancer. *PLoS One*, 13(5):e0196763, 2018.

[33] Irena Andršová, Katerina Hnatkova, Martina Šišáková, Ondřej Toman, Peter Smetana, Katharina M Huster, Petra Barthel, Tomáš Novotnỳ, Georg Schmidt, and Marek Malik. Influence of heart rate correction formulas on qtc interval stability. *Scientific Reports*, 11(1):14269, 2021.

[34] Song-Kyoo Kim, Chan Yeob Yeun, Paul D. Yoo, Nai-Wei Lo, and Ernesto Damiani. Deep learning-based arrhythmia detection using rr-interval framed electrocardiograms, 2020.

[35] Shourya Verma. Development of interpretable machine learning models to detect arrhythmia based on ecg data, 2022.

[36] Xiaopeng Zhao. Indeterminacy of spatiotemporal cardiac alternans, 2008.

[37] Kratika Tyagi and Prof. Sanjeev Thakur. A survey on various data mining techniques for ecg meta analysis, 2016.

[38] Qiang Zhu, Xin Tian, Chau-Wai Wong, and Min Wu. Ecg reconstruction via ppg: A pilot study, 2019.

[39] Zeynab Samandari and Seyyedeh Fatemeh Molaeezadeh. Towards bloodless potassium measurement from ecg using neuro-fuzzy systems, 2023.

[40] Abhinandan Panda, Srinivas Pinisetty, and Partha Roop. Runtime monitoring and statistical approaches for correlation analysis of ecg and ppg, 2022.

[41] Atit Pokharel, Shashank Dahal, Pratik Sapkota, and Bhupendra Bimal Chhetri. Electrocardiogram (ecg) based cardiac arrhythmia detection and classification using machine learning algorithms, 2024.

[42] T. R. Gopalakrishnan Nair, A. P. Geetha, and Asharani. Methodology for detection of qrs pattern using secondary wavelets, 2014.

[43] Dharma KC, Chicheng Zhang, Chris Gniady, Parth Sandeep Agarwal, and Sushil Sharma. Sim-ecg: A signal importance mask-driven ecgclassification system, 2021.

[44] Li Xiaolin, Fang Xiang, Rajesh C. Panicker, Barry Cardiff, and Deepu John. Classification of ecg based on hybrid features using cnns for wearable applications, 2022.

[45] Wenqi Guan. An electrocardiogram monitoring device based on stm32, 2024.

[46] Swati Banerjee and Madhuchhanda Mitra. Classification of st and q type mi variant using thresholding and neighbourhood estimation method after cross wavelet based analysis, 2013.

[47] Manuel Pazos-Santomé, Fernando Martín-Rodríguez, and Mónica Fernández-Barciela. Automated optical reading of scanned ecgs, 2024.

[48] Omer Belhasin, Idan Kligvasser, George Leifman, Regev Cohen, Erin Rainaldi, Li-Fang Cheng, Nishant Verma, Paul Varghese, Ehud Rivlin, and Michael Elad. Uncertainty-aware ppg-2-ecg for enhanced cardiovascular diagnosis using diffusion models, 2024.

[49] Elena Zappon, Matthias A. F. Gsell, Karli Gillette, and Gernot Plank. Quantifying variabilities in cardiac digital twin models of the electrocardiogram, 2024.

[50] Sajad Mousavi, Fatemeh Afghah, and U. Rajendra Acharya. Inter- and intra- patient ecg heartbeat classification for arrhythmia detection: a sequence to sequence deep learning approach, 2019.

[51] Paola Kamga, Rasik Mostafa, and Saba Zafar. The use of wearable ecg devices in the clinical setting: a review. *Current emergency and hospital medicine reports*, 10(3):67–72, 2022.

[52] Jérôme Van Zaen, Ricard Delgado-Gonzalo, and Damien Ferrario Mathieu Lemay. Cardiac arrhythmia detection from ecg with convolutional recurrent neural networks, 2020.

[53] M. Bazarghan, Y. Jaberi, R. Amandi, and M. Abedi. Automatic ecg beat arrhythmia detection, 2012.

[54] Geoffrey H. Tison, Jeffrey Zhang, Francesca N. Delling, and Rahul C. Deo. Automated and interpretable patient ecg profiles for disease detection, tracking, and discovery, 2018.

[55] Ridwan Alam, Aaron Aguirre, and Collin Stultz. Detecting qt prolongation from a single-lead ecg with deep learning, 2023.

[56] Luca Neri, Matt T Oberdier, Kirsten CJ van Abeelen, Luca Menghini, Ethan Tumarkin, Hemantkumar Tripathi, Sujai Jaipalli, Alessandro Orro, Nazareno Paolocci, Ilaria Gallelli, et al. Electrocardiogram monitoring wearable devices and artificial-intelligence-enabled diagnostic capabilities: a review. *Sensors*, 23(10):4805, 2023.

[57] Mohamed Hammad, Rajesh NVPS Kandala, Amira Abdelatey, Moloud Abdar, Mariam Zomorodi-Moghadam, Ru San Tan, U Rajendra Acharya, Joanna Pławiak, Ryszard Tadeusiewicz, Vladimir Makarenkov, et al. Automated detection of shockable ecg signals: A review. *Information Sciences*, 571:580–604, 2021.

[58] Deyun Zhang, Shijia Geng, Yang Zhou, Weilun Xu, Guodong Wei, Kai Wang, Jie Yu, Qiang Zhu, Yongkui Li, Yonghong Zhao, Xingyue Chen, Rui Zhang, Zhaoji Fu, Rongbo Zhou, Yanqi E, Sumei Fan, Qinghao Zhao, Chuandong Cheng, Nan Peng, Liang Zhang, Linlin Zheng, Jianjun Chu, Hongbin Xu, Chen Tan, Jian Liu, Huayue Tao, Tong Liu, Kangyin Chen, Chenyang Jiang, Xingpeng Liu, and Shenda Hong. Artificial intelligence system for detection and screening of cardiac abnormalities using electrocardiogram images, 2023.

[59] Sumukh Vasisht Shankar, Evangelos K Oikonomou, and Rohan Khera. Cards-plus ecg platform: Development and feasibility evaluation of a multiplatform artificial intelligence toolkit for portable and wearable device electrocardiograms, 2023.

[60] Mohamed Adel Serhani, Hadeel T. El Kassabi, Heba Ismail, and Alramzana Nujum Navaz. Ecg monitoring systems: Review, architecture, processes, and key challenges. *Sensors*, 20(6):1796, 2020.

[61] Tomofumi Kimotsuki, Noriko Niwa, Martin N. Hicks, Michael Dunne, Stuart M. Cobbe, and Mari A. Watanabe. Isoprenaline increases excursive restitution slope in the conscious rabbit with ischaemic heart failure, 2009.

[62] Yuexin Bian, Jintai Chen, Xiaojun Chen, Xiaoxian Yang, Danny Z. Chen, and JIan Wu. Identifying electrocardiogram abnormalities using a handcrafted-rule-enhanced neural network, 2022.

[63] Tim Julian Möller, Martin Voss, and Laura Kaltwasser. An arduino based heartbeat detection device (ardmob-ecg) for real-time ecg analysis, 2022.

[64] Tsai-Min Chen, Yuan-Hong Tsai, Huan-Hsin Tseng, Kai-Chun Liu, Jhih-Yu Chen, Chih-Han Huang, Guo-Yuan Li, Chun-Yen Shen, and Yu Tsao. Srecg: Ecg signal super-resolution framework for portable/wearable devices in cardiac arrhythmias classification, 2023.

[65] Ivo Pascal de Jong, Andreea Ioana Sburlea, and Matias Valdenegro-Toro. Uncertainty quantification in machine learning for biosignal applications – a review, 2023.

[66] S. Karpagachelvi, M. Arthanari, and M. Sivakumar. Ecg feature extraction techniques - a survey approach, 2010.

[67] Shenda Hong, Yuxi Zhou, Junyuan Shang, Cao Xiao, and Jimeng Sun. Opportunities and challenges of deep learning methods for electrocardiogram data: A systematic review, 2020.

[68] Marko Velic, Ivan Padavic, and Sinisa Car. Computer aided ecg analysis - state of the art and upcoming challenges, 2013.

[69] Melle B. Vessies, Sharvaree P. Vadgama, Rutger R. van de Leur, Pieter A. Doevendans, Rutger J. Hassink, Erik Bekkers, and René van Es. Interpretable ecg classification via a query-based latent space traversal (qlst), 2021.

[70] Ecg beat classification using machine learning and pre-trained convolutional neural networks.

Disclaimer:

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.

AI-generated, for reference only.