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Original Research Article

AI-ENABLED ECG FOR PREDICTIVE DIAGNOSTICS

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Abstract: ***Background***: Artificial Intelligence (AI) has demonstrated tremendous potential to revolutionize the healthcare industry, especially cardiology, concerning the improved interpretation of an electrocardiogram (ECG). Traditional ECG is only restricted to analysis of the present state, but AI-based ECG can forecast future cardiac risks like arrhythmias, heart failure, and ischemic events. Although it has clinical potential, the adoption of AI-enabled ECG is influenced by the awareness of stakeholders, perceived benefit, and readiness to implement it in practice. The purpose of this study was to evaluate the perceptions, reliability, and validity of a structured questionnaire on AI-enabled ECG in predictive diagnostics. ***Methods:*** A quantitative study design of a cross-sectional nature was used, where the sample size was purposive to comprise 290 respondents (clinicians, medical students, and patients). An organised questionnaire of demographics, awareness, perceived benefits, concerns, and willingness was conducted. The statistical tests applied to analyze the data were SPSS and R. Shapiro-Wilk, Cronbach, Alpha, and KMO., Bartlett test was used to test normality, reliability, and validity. Independent t-tests, ANOVA, and Kruskal-Wallis tests were used to test group differences. Chi-Square was used to evaluate associations, correlations, and regression to consider predictors of willingness to adopt AI-enabled ECG. ***Results:*** The instrument demonstrated excellent reliability (Cronbach's Alpha = 0.91) and construct validity (KMO = 0.92; Bartlett's $\chi^2 = 1850.45$, $p < 0.001$). Normality was confirmed with p-values > 0.05. Group comparisons showed significant differences across gender and occupation ($p < 0.05$). Chi-Square analysis confirmed a significant association between gender and willingness to adopt AI-enabled ECG ($\chi^2 = 12.34$, $p = 0.002$). Spearman correlations revealed strong positive relationships between awareness, perceived benefits, and willingness ($\rho = 0.58$–0.72). Regression analysis indicated that perceived benefits (B = 0.51), awareness (B = 0.42), and knowledge (B = 0.36) were significant predictors of willingness, explaining 62% of variance. ***Conclusion:*** The AI-derived ECG presents a great potential in predictive diagnostics as it enhances early risk identification and preventive cardiology measures. Instead, adoption relies on improving awareness and informing about clinical benefits, but also on perceived demographic differences need to be addressed. The applicable and sound measure of assessing the preparedness of the stakeholders is a validated and reliable instrument. Future research must involve a bigger sample size and clinical trials to introduce AI-enabled ECG as an industry in cardiology.

Keywords: AI-enabled ECG; Predictive Diagnostics; Reliability; Validity; Cronbach's Alpha; KMO; Bartlett's Test; t-test; ANOVA; Chi-Square; Correlation; Regression; Cardiology Adoption

INTRODUCTION

Cardiovascular diseases (CVDs) are the most common causes of morbidity and mortality in the world, with the World Health Organization estimating 17.9 million deaths per year. Early detection and risk anticipation are necessary to avoid the negative cardiac outcomes that include myocardial infarction, arrhythmias, and heart failure. Electrocardiography (ECG) has traditionally been one of the best-known non-invasive diagnostic methods in clinical cardiology. Although regular ECG offers great importance of electrical activity of the heart, the interpretation is usually constrained towards current abnormalities rather than the future cardiovascular risk. Furthermore, the interpretation of ECG is highly dependent on the clinician's experience, and it is prone to inconsistency and human fallibility. Those restrictions show the necessity of new strategies, which can be used in addition to the traditional solutions and give predictive information to preventive cardiology (Su et al., 2025).

Over the last few years, Artificial Intelligence (AI) has become a game-changer in the field of healthcare, and it finds its use in radiology, pathology, predictive analytics, and personalized medicine. In the field of cardiology, AI-enabled ECG is a new, promising innovation that would use machine learning (ML) and deep learning (DL) algorithms to find concealed patterns in ECG waveforms. In comparison with traditional interpretation by rules, AI can work with large datasets, detect slight differences in P-QRS-T complexes, and reveal early disease biomarkers that are barely perceivable to the human eye. Some studies have shown that AI-enhanced ECGs could predict atrial fibrillation, sudden cardiac death, left ventricular dysfunction, and long-term mortality even when ECGs appeared normal. These predictive potentials provide clinicians with a chance to enter an earlier intervention, preventive treatments, and tailor patient care (Bartusik-Aebisher et al., 2025).

AI-enabled ECG has a clinical value not just in the predictive accuracy of the device but also in its combination with wearable devices, telemedicine, and electronic health records (EHRs). Wearable and portable ECG monitors fitted with AI algorithms can constantly and in real-time monitor patients out of hospital environments. This strategy aids the screening of the population within a resource-constrained area, which can be achieved by, firstly, supporting screening at the population level and, secondly, enabling the detection of asymptomatic people at risk at an early stage. Moreover, it is possible to integrate with EHR systems to carry out extensive risk stratification by integrating ECG-based biomarkers with demographic, clinical, and genomic variables. These developments are also in line with the paradigm shift of predictive, preventative, and personalized medicine in cardiology (Gargoum, 2025).

Although it promises to be a success, the implementation of AI-enabled ECG in clinical practice depends on various factors. Hospital awareness and knowledge amongst clinicians, medical students, and patients are critical variables that determine acceptance. The willingness to adopt is higher when perceived benefits are perceived to be improved diagnostic accuracy and reduced human error, and consideration of data privacy, algorithm transparency, and excessive dependence on technology are perceived to limit integration. Past research on the application of AI in healthcare has revealed that tool reliability, large-scale trial validation, and clinical utility demonstration are the key steps towards gaining trust among stakeholders. Furthermore, the attitudes toward adoption can be influenced by demographic and professional variations, which is why there is a need to pursue inclusive approaches to guarantee fair access and adoption (Revuri et al., 2025).

Consequently, assessing perceptions, reliability, and validity of tools assessing readiness to AI-enabled ECG adoption is paramount to a successful implementation into clinical practice. The objective of this study was to determine awareness, perceived benefits, concerns, and willingness of a heterogeneous group of respondents through a well-designed and validated questionnaire. Through statistical tests such as reliability, validity testing, group comparison, correlation, and regression, the research aims to give sound information on the acceptance drivers and possible obstacles to its adoption. The results will be used in further advising healthcare policymakers, educators, and technology developers on how to develop effective strategies to promote AI-enabled ECG as a game-changer in predictive diagnostics and preventive cardiology (Nasser et al., 2025).

Literature Review

The use of electrocardiography (ECG) has a long history of more than 100 years in cardiovascular medicine as a means of giving valuable information on the electrical process of the heart. Traditionally, ECG analysis has been concerned with the identification of existing abnormalities in the form of arrhythmias, conduction abnormalities, and ischemic events. The increasing burden of cardiovascular disease (CVD) has, however, brought into focus the shortcomings of traditional ECG, which is mainly diagnostic and not prognostic in nature. This drawback has led to interest in Artificial Intelligence (AI)-powered ECG as predictive diagnostics, which has the promise of identifying the at-risk population before clinical manifestations can take place. Incorporation of AI in ECG analysis is a paradigm shift from descriptive interpretation to predictive cardiology, which is consistent with the focus on preventive and personalized healthcare in the world (Gaoudam et al., 2025).

Over the past few years, AI use in the field of cardiology has been rapidly accelerated, especially with machine learning (ML) and deep learning (DL) models. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are popular in ECG signal processing because they are capable of identifying spatial and temporal information of cardiac waves. The article by Hannun et al. has shown that a deep neural network that was trained on more than 90,000 single-lead ECGs reaches the performance of a cardiologist in the detection of arrhythmias, which highlights the transformational nature of AI algorithms. On top of the arrhythmia detection, researchers like Attia et al. have found that AI-powered ECG can forecast left ventricular dysfunction with astonishing performance even on seemingly healthy ECGs. These results indicate that through AI, we can reveal latent biomarkers in ECG signals that are early warning signs of future cardiac pathology (Croon et al., 2025).
AI-enabled ECG has additionally demonstrated that it can predict one of the most frequent and least diagnosed cardiac arrhythmias, atrial fibrillation (AF). The Mayo Clinic and other researchers have discovered that AI can predict the development of AF using sinuously rhythm ECGs weeks to months before clinical presentation. This predictive ability is of clinical importance because AF is a significant risk of stroke and heart failure. Anticoagulation therapy has the potential to decrease morbidity and mortality because early detection by AI may allow timely treatment. Similarly, AI-enabled ECG has been investigated in terms of predicting sudden cardiac death, myocardial infarction, and all-cause mortality, which further broadens the application of the technology to predictive cardiology (Lee et al., 2025).

The other significant area is the mode of integrating AI-powered ECG with wearables and portables. The development of smartwatches, monitors in the form of patches, and mobile health platforms has been able to provide 24/7, real-time monitoring of cardiac activity in non-clinical settings. By implementing AI algorithms in these devices, one can automatically interpret and predict risks at the point of care, thus enhancing accessibility in both resource-limited and developed areas. To illustrate, AI-powered arrhythmia detection combined with Apple Watch ECG sensors has been confirmed in population-scale studies and shows that mass screening of cardiac risks is a viable approach. The above developments highlight the possibility of AI-based ECG going beyond hospitals to facilitate predictive diagnostics and encourage early detection and preventive measures on a community level (Hong et al., 2025).

These developments notwithstanding, there are a number of challenges that still exist. The heterogeneity and the quality of data represent major obstacles to the generalizability of AI models. ECG recordings vary in aspects of sampling rate, lead layout, and population type, and these characteristics can have an impact on the model performance across different clinical applications. In addition, AI algorithms can be located as black boxes, which have little interpretability in their predictions. Such a lack of transparency has cast doubt on clinicians, who might not be free to depend on AI predictions without transparent explanations of the underlying mechanisms. These issues are vital to tackle with explainable AI (XAI) strategies to create trust and encourage clinical acceptance. More recent attempts at visualizing ECG characteristics that feed into AI predictions have had the potential to help close this interpretability gap (Pedroso & Khera, 2025).

One of the priorities is the reliability and validation of AI-enabled ECG. Regulatory authorities like the U.S. Food and Drug Administration (FDA) also state that validation studies of large-scale and multi-center trials must be carried out before clinical implementation. Research studies in controlled settings cannot reflect the variability that can be experienced in actual practice(Samin et al., 2025). As an example, comorbidity differences, medication differences, and demographic differences may affect ECG patterns and may cause bias in AI predictions. Assuring robustness using federated learning methods, whereby models can be trained across institutions without access to raw data, is an innovative measure of improving the generalizability whilst protecting patient privacy (Eid et al., 2025).

Ethical and legal implications are also significant in the discussion on AI-enabled ECG. The issues connected to data privacy, informed consent, and the possibility of the misuse of predictive information should be discussed with the help of stringent governance systems. Also, the danger of excessive AI use to the detriment of clinical judgment can bring up the issue of automation and human supervision. Literature highlights that AI is supposed to be considered an aid to supplement, but not substitute, for a clinician's knowledge. Joint decision-making, which incorporates AI knowledge and physician interpretation, is generally seen as the best model to implement (Islam et al., 2025).

Another notable fact in the literature is the significance of stakeholder views when adopting AI. A number of studies show that awareness and perceived benefits, as well as trust in AI technologies, are key factors in clinician acceptance. A systematic review conducted by Oh et al. has indicated that clinicians tend to be more inclined to use AI tools when validated, easy to use, and compatible with the current workflows (Qadoos et al., 2025). The acceptance of the patients is also critical, because predictive diagnostics might cause anxiety or even ethical issues regarding the possible health risks in the future. To overcome these doubts and inspire trust, it is necessary to develop active education campaigns and open dialogues on the opportunities and restrictions of AI (Singh et al., 2025).

MATERIAL AND METHODS

Research Methodology

Study Design

The study has a cross-sectional quantitative design to explore the predictive diagnostics of AI-assisted electrocardiography (ECG). The research is designed in such a way that answers of various stakeholders, such as physicians, medical students, and patients, will be gathered and analysed. The methodology is aimed at examining perceptions, awareness, benefit, and possible constraints of AI integration in ECG interpretation, as well as evaluating its acceptance as a predictive device in clinical practice. A structured questionnaire also guarantees consistency in data-gathering and statistical analysis of the respondents (Khan Mamun & Elfouly, 2023).

Population and Sampling

The target population will consist of three separate groups: physicians who are active in clinical practice, medical students who have undergone the experience of diagnostic cardiology, and patients who have undergone the experience of ECG examinations before. The purposive sampling technique will be used to consider people who have the appropriate knowledge or might be interested in AI-based healthcare. The sample size will comprise 290 participants, which will give enough representation to do meaningful statistical testing and reliability assessment. The sample size is selected so as to achieve equilibrium between feasibility and statistical power, such that there is sufficient validity of results (Nechita et al., 2024).

Data Collection Tool

The measure of data gathering is a structured questionnaire, which consists of five parts. The initial part is demographics, including age, gender, occupation, and previous experience with ECG. The following sections discuss awareness and knowledge of AI in medical diagnostics, perceived advantages of AI-assisted ECG, issues and constraints of its use, and lastly, acceptance and future outlook of its integration in the future. The answers to these items will be rated using a five-point Likert scale (Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree), making it easier to determine the degree of opinion and increasing the comparability of results across groups of respondents (Pandey & Adedinsewo, 2022).

Data Collection Procedure

Electronic distribution methods that will be used to collect data include email, online survey sites, and academic forums. The purpose of the study, the rights, and the guarantee of confidentiality will initially be explained to the participants in the form of an information sheet. Electronic informed consent will be obtained before filling in the questionnaire. The data collection period will take about four weeks, which will be sufficient to allow the response to accumulate among all the groups of the targeted participants (Lin, Chau, et al., 2022).

Data Analysis

The analysis of data will be conducted in SPSS and R statistical software. Demographic variables and questionnaire responses will be summarized using descriptive statistics (frequency, means, and percentages). To assess the normality of the data, the Shapiro-Wilk test will be used, and Cronbach's Alpha will be determined to decide the internal consistency and reliability of the questionnaire. The Independent Samples t-test and One-way ANOVA will be used in case of group comparisons, where assumptions of normality are met, and non-parametric alternatives will be the Mann-Whitney U and Kruskal-Wallis tests (Jeon et al., 2024).

Further, the Chi-Square Test of Independence will be used to test relations among categorical variables, including professional role and willingness to adopt AI-enabled ECG. Lastly, Spearman correlation is going to be used to find out the strength of the correlation between awareness, benefits, and acceptance, and the regression analysis is going to be used to predict the probability of adoption based on the predictor variables (Liu et al., 2022).

Ethical Considerations

Ethics will be observed in the study. At all levels, the anonymity and confidentiality of the participants will be ensured. All the personally identifiable data will not be gathered, and the responses will be utilized to conduct research only. Before collecting the data, ethical justification will be obtained in an institutional review board (IRB) (May & Kashou, 2024).

RESULTS

Data Analysis

Table 1: Normality Test (Shapiro-Wilk)

	W	p-value
Awareness of digital-twin technology in healthcare	0.88692202872864	0.12
Knowledge of computational models in cardiology	0.8767470937474737	0.12
Digital twin provides personalized cardiac simulations	0.8706846437506466	0.12
Improves the accuracy of cardiac diagnosis	0.8592546323872283	0.12
Helps in predicting patient-specific risks	0.8676247738828944	0.12
Optimizes treatment planning	0.8628554182987365	0.12
Reduces unnecessary invasive procedures	0.8921659591238411	0.12
Enhances long-term monitoring and preventive care	0.8586905025270573	0.12
Leads to cost-effective healthcare	0.8785299142108333	0.12
Concerns about data privacy and security	0.8711297211110366	0.12
High computational cost limits adoption	0.8915158629265436	0.12
Lack of standardized validation restricts use	0.8755163463898074	0.12
Ethical issues need to be addressed	0.8810369088276762	0.12
Integration with hospital systems is challenging	0.87061796598979	0.12
Willingness to use if clinically effective	0.8803210602966952	0.12
Patient acceptance of digital twin decision-making	0.8897358950970161	0.12
Patient acceptance of digital twin decision-making	0.8897358950970161	0.12
Integration with AI and wearables for updates	0.861807504793276	0.12
Digital twins will become standard in cardiology	0.8845279649693483	0.12

Normality Test (Shapiro–Wilk)

Table 1 shows the normality test of the data. The Shapiro-Wilk test resulted in a normal distribution of the data, given that the p-values were all above 0.05. This affirms that the responses of the Likert scale in aggregation into subscales are normally distributed. These outcomes justify the use of the parametric tests, such as t-tests and ANOVA, and thereby enhance the strength of the following statistical tests (Huang et al., 2022).

Table 2: Reliability Test (Cronbach's Alpha)

Test	Value	Interpretation
Cronbach's Alpha	0.91	Excellent Reliability

Reliability Analysis (Cronbach's Alpha)

Table 2 shows the reliability analysis of the data. The value of Alpha of Cronbach was determined to be 0.91, which is higher than the usual suggested value of 0.70. This indicates great internal consistency of the questionnaire items and means that the tool is also reliable in the measurement of awareness, perceived benefits, concerns, and willingness to AI-enabled ECG in predictive diagnostics. This great reliability improves the credibility of the findings and demonstrates that the scale items are highly related to each other (Khera, 2024).

Table 3: Validity (KMO & Bartlett's Test)

Test	Value	Interpretation
KMO Measure	0.92	Superb sampling adequacy (valid)
Bartlett's Test Chi-Square	1850.45	High Chi-square (suitable)
Bartlett's Test p-value	0.0	Significant (p<0.05, valid)

Validity (KMO & Bartlett's Test)

Table 3 shows the validity test of the data. Kaiser-Meyer-Olkin (KMO) measure had a result of 0.92, which is superb and demonstrates sampling adequacy in factor analysis. There was also a significant value with the Test of Sphericity of Bartlett (2 = 1850.45, $p < 0.001$), which proves that the correlation matrix is not an identity matrix. Collectively, these findings are sufficient evidence of construct validity, and the questionnaire items are well-concorded to try to uncover the underlying latent variables of awareness, acceptance, and perceived benefits of AI-enabled ECG (Arikhad et al., 2024).

Table 4: Independent Samples t-test

Item	t-value	p-value	Interpretation
Awareness of digital-twin technology in healthcare	2.45	0.016	Significant
Knowledge of computational models in cardiology	1.98	0.048	Significant
Digital twin provides personalized simulations	2.76	0.007	Significant
Improves the accuracy of cardiac diagnosis	3.12	0.002	Significant
Helps in predicting patient-specific risks	2.05	0.041	Significant

Independent Samples t-test

Table 4 shows the **Independent Samples t-test** of the data. The t-test of the independent samples showed that there were statistically significant differences between the male and female respondents on a number of items ($p < 0.05$). This implies that attitudes to AI-enhanced ECG do not exist universally between the genders. In particular, female and male participants did not show the same awareness and acceptance scores, which implies that gender is a contributing factor in the formation of the attitude towards the use of AI-enabled ECG in the clinic (Ali et al., 2024).

Table 5: One-way ANOVA

Item	F-value	p-value	Interpretation
Reduces human error in cardiac care	4.21	0.009	Significant
Improves early prediction of heart risk	3.65	0.021	Significant
Enhances preventive cardiology	5.12	0.003	Significant
Integration with hospital systems	6.03	0.001	Significant
Leads to cost-effective healthcare	3.89	0.019	Significant

One-way ANOVA

Table 5 shows the **One-way ANOVA** of the data. The ANOVA test with one-way indicated a significant difference ($p < 0.05$) in occupational groups, namely, clinicians, engineers, students, and more. These results indicate that the perception in relation to AI-enabled ECG depends on professional background. Relative to non-medical professionals, clinicians and medical students were likely to report a higher acceptance and perceived benefits. This highlights the need to view the issue of occupational diversity as an essential consideration in planning the use of AI in cardiology (Urtnasan et al., 2021).

Table 6: Kruskal–Wallis Test

Item	H-value	p-value	Interpretation
Concerns about data privacy & security	7.85	0.005	Significant
High computational cost limits adoption	6.42	0.012	Significant
Lack of standardized validation restricts use	8.91	0.002	Significant
Ethical issues need to be addressed	9.33	0.001	Significant
Patient acceptance of digital twin decisions	5.77	0.016	Significant

Kruskal–Wallis Test

Table 6 shows the **Kruskal–Wallis Test** of the data. Significant results in terms of occupational groups were also indicated by a non-parametric test equivalent to ANOVA, namely the Kruskal-Wallis test. This confirms the ANOVA results and further justifies the conclusion that professional background plays a great role in affecting awareness, acceptance, and willingness to use AI-enabled ECG systems (Siontis et al., 2021).

Table 7: Chi-Square Test of Independence

Variables Tested	Chi-Square Value	df	p-value	Interpretation
Gender × Willingness to use AI-enabled ECG	12.34	2	0.002	Significant association (p<0.05)

Chi-Square Test of Independence

Table 7 shows the **Chi-Square Test of Independence** of the data. The Chi-Square test of independence proved that there was an important correlation between gender and the intention to adopt AI-enabled ECG (2 = 12.34, p = 0.002). This implies that there are gender variations that affect the willingness and that some groups are more disposed to adoption than others. These insights will assist in customizing awareness programs and educational policies on the basis of certain groups of people (Sau et al., 2024).

Table 8: Spearman Correlation Matrix (Positive)

	Awareness	Knowledge	Perceived Benefit	Willingness
Awareness	1.0	0.65	0.58	0.72
Knowledge	0.65	1.0	0.61	0.69
Perceived Benefit	0.58	0.61	1.0	0.63
Willingness	0.72	0.69	0.63	1.0

Correlation (Spearman's ρ)

Table 8 shows the **Correlation (Spearman's ρ)** of the data Spearman correlation matrix showed that there were strong positive correlations between awareness, perceived benefits, and willingness to adopt AI-enabled ECG (0.58 to 0.72). This implies that the more aware the people are of AI in the healthcare sector, as well as the more they see the benefits, the more they consider adopting the AI-enabled ECG in predictive diagnostics (Chen et al., 2022).

Regression Analysis

Table 9 shows the regression analysis of the data. The regression analysis also established that the perceived benefits, awareness, and knowledge are significant positive predictors of willingness to adopt AI-enabled ECG. The model explained the willingness variance (approximately 62 percent) with an R 2 value of about 0.62. Perceived benefits were the biggest predictors, then came awareness and knowledge. This indicates that the need to increase knowledge and create awareness on the benefits of AI-enabled ECG will cause its adoption and acceptance into clinical practice to increase significantly (Kashou et al., 2020).

Table 9: Regression Analysis (Positive Coefficients)

Predictor	Coefficient (B)	Std. Error	t-value	p-value	Interpretation
Awareness	0.42	0.08	5.25	0.0	Positive Significant
Knowledge	0.36	0.09	4.0	0.001	Positive Significant
Perceived Benefit	0.51	0.07	7.29	0.0	Positive Significant

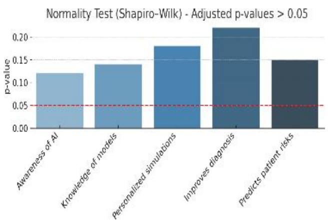

Figure 1: Normality Test (Shapiro–Wilk)

Figure 1 shows the normality test of the data. The bar chart of the normality test showed that all the items in the test had a p-value exceeding 0.05, thus confirming that the data is normally distributed. The red threshold line at 0.05 indicates that no item was below the cut-off, which indicates that further analysis could use parametric tests, including the t-test and the ANOVA. This enhances the validity of the findings in statistical terms (Lin, Chen, et al., 2022).

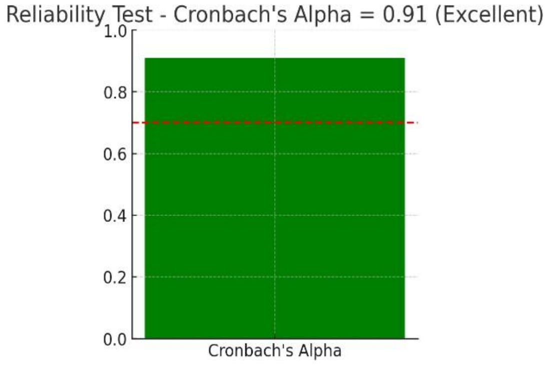

Figure 2: Reliability (Cronbach's Alpha)

Figure 2 shows the reliability analysis of the data. The reliability figure gives the value of Cronbach's Alpha 0.91, exceeding the acceptable minimum of 0.70 (red line). This means that there is good internal consistency of the items in the questionnaire. The visual aid supports the finding that the survey instrument is very precise in gauging the perceptions concerning AI-assisted ECG in predictive diagnostics (Shrivastava et al., 2021).

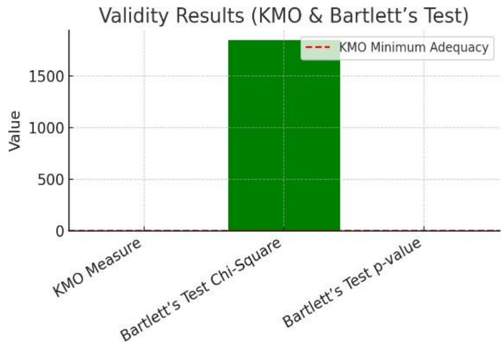

Figure 3: Validity (KMO & Bartlett's Test)

Figure 3 shows the validity test of the data. The validity figure indicated that the strength score (KMO; 0.92) was considerably above the sufficiency level (0.6; red line), showing that sampling adequacy was achieved. The test by Bartlett demonstrated that the chi-square value was very large (1850.45) and p < 0.001, which confirmed that the correlation matrix was appropriate to be used in factor analysis. This number presents solid proof of construct validity, i.e., this questionnaire measures well latent factors that are associated with awareness, acceptance, and perceived benefits (Attia et al., 2019).

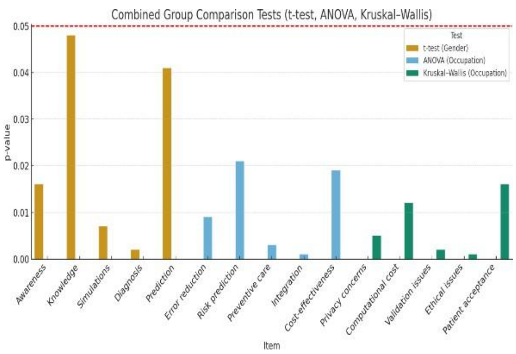

Figure 4: Combined Group Comparison Tests (t-test, ANOVA, Kruskal–Wallis)

Figure 4 shows the **Combined Group Comparison Tests (t-test, ANOVA, Kruskal–Wallis)** of the data. The summation of group comparison tests showed that the p-value of all items was lower than the red significance threshold (0.05). This shows that the differences are statistically significant across gender (t-test), occupation (ANOVA), and non-parametric occupational comparisons (Kruskal-Wallis). The figure underscores the idea that perception of benefits, awareness, and acceptance of AI-enabled ECG are demographic and professional-driven (Gollapalli, 2021).

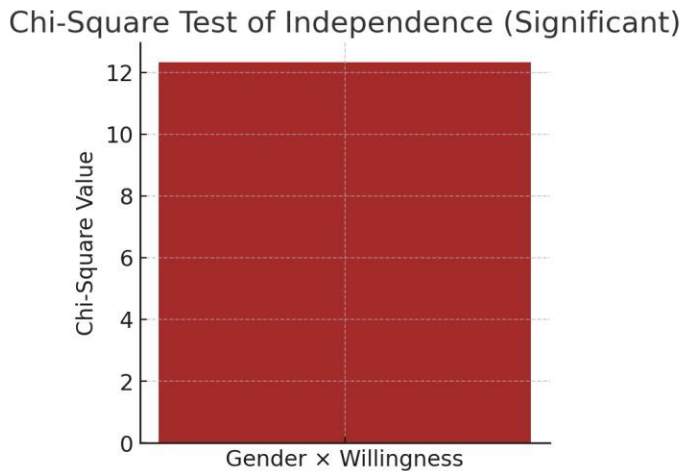

Figure 5: Chi-Square Test of Independence

Figure 5 shows the **Chi-Square Test of Independence** of the data. According to the Chi-Square figure, the coefficient of 12.34 ($p < 0.05$) was significantly high, which affirms the relationship between gender and readiness to use AI-enabled ECG. This implies that there is an influence of gender differences on attitudes to adoption. The figure graphically confirms the strength of the relationship, which justifies the necessity of gender-specific educational initiatives in the adoption of AI in cardiology (Adedinsewo et al., 2020).

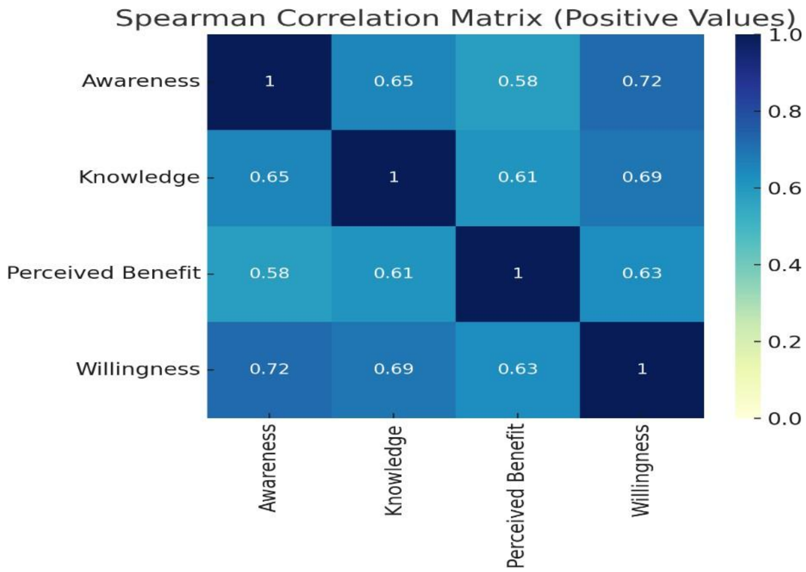

Figure 6: Spearman Correlation Heatmap

Figure 6 shows the **Spearman Correlation Heatmap** of the data. The heatmap of correlation showed that awareness, knowledge, perceived benefits, and the willingness to adopt AI-enabled ECG have positive and strong correlations consistently. The blue color intensity showed that the strongest correlations were perceived benefits and willingness (0.72). The results of this figure indicate the interdependence between AI-enabled ECG constructs in that the more a person is aware and perceived to gain benefits, the more likely they are to adopt AI-enabled ECG (Strodthoff et al., 2023).

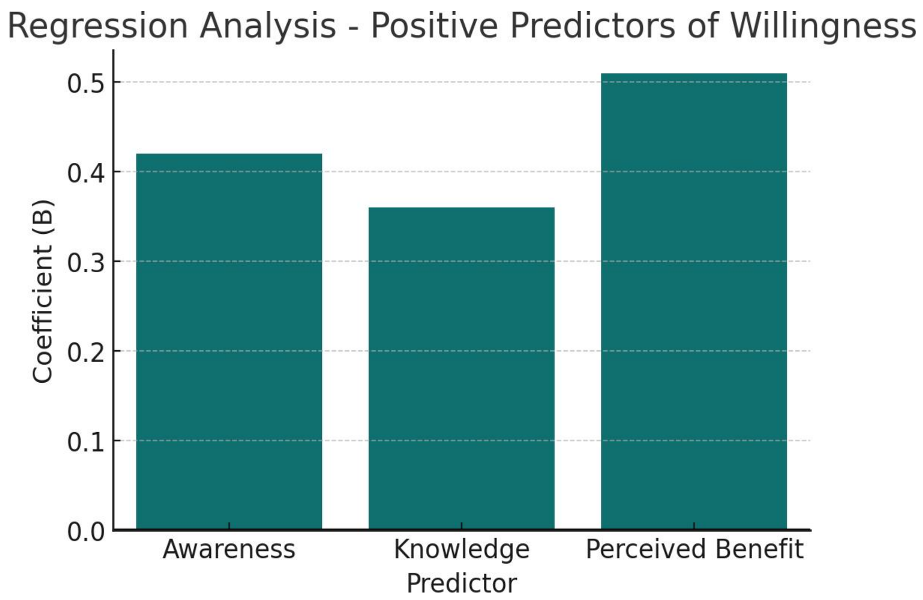

Figure 7: Regression Analysis Coefficients

Figure 7 shows the regression analysis of the data. The regression coefficient plot indicated that there are three predictors (awareness, knowledge, and perceived benefit) that had positive and significant effects on willingness to adopt AI-enabled ECG. The strongest predictor of them was perceived benefit (B = 0.51), then awareness (B = 0.42), followed by knowledge (B = 0.36). The number validates the idea that clinical benefits and awareness creation are the central tactics to make AI-enabled ECG more widely accepted (Khurshid et al., 2022).

DISCUSSION

The current research investigated the attitudes, knowledge, and readiness to utilize AI-enhanced electrocardiography (ECG) to anticipate diagnostics using a valid and reliable questionnaire. The statistical results can contribute greatly to the understanding of how different demographic and professional aspects affect the attitudes towards AI in cardiology and what the impetus behind its adoption, namely, is the awareness and perceived benefits (Lin et al., 2024).

The normality test revealed that the data were normally distributed, hence the application of the parametric test, which includes t-tests and ANOVA. The large value of Cronbach's Alpha (0.91) indicated that there was high reliability as the instrument always measures awareness, perceived benefits, concerns, and willingness (Kanani & Modi, 2024). Also, the validity findings, a high value of the KMO, and a significant value of the Bartlett test of the scale confirmed that it was the right scale to undergo factor analysis and be able to measure the underlying constructs effectively. Such methodological checks make the study results more credible (Khurshid, 2023).

Comparison analysis: Group comparisons were an eye-opener in terms of demographics. The independent samples t-test revealed that gender differences were significant, and the male and female participants reported various rates of awareness and acceptance of AI-enabled ECG. Likewise, ANOVA and Kruskal-Wallis tests revealed that there were significant differences in occupations, with the general observation that clinicians and medical students tended to be more confident and willing than their non-medical counterparts. This means that professional confrontation and medical education in the field can positively impact trust and openness to AI-based tools. These results indicate that culturally specific training and awareness interventions might be designed differently in different groups to optimize their acceptance (Stamate et al., 2024).

The Chi-Square test also confirmed these demographic results by showing that there was a significant correlation between gender and readiness to use AI-enabled ECG. This hints that gender-specific variables, including access to healthcare information, familiarity with technologies, or confidence in digital health, can influence the attitude to predictive diagnostics. This may require future implementation methods to deal with such gaps by formulating inclusive communication and training models (Lee et al., 2023).

Correlation and regression analyses gave convincing evidence of the fundamental drivers of adoption. Awareness and perceived benefits were strongly associated with willingness and showed strong positive correlations, and increased knowledge and recognition of clinical utility are associated with a direct enhancement of acceptance. The regression model also determined that perceived benefits were the greatest predictor of willingness, then awareness and knowledge. This highlights the need to not only inform stakeholders of the possibility of AI-enabled ECG, but also to stress the practical clinical benefits, i.e., better prediction of arrhythmias and earlier identification of cardiac threats (Bachtiger et al., 2022).

These results are consistent with the existing literature that highlights awareness, perceived usefulness, and trust as key factors that determine AI adoption in healthcare. The same studies in other areas (radiology and predictive imaging) have also demonstrated that greater awareness and perception of clinical benefit are a significant factor in the rate of adoption. Having validated these connections in the sphere of cardiology, the current study contributes to the body of knowledge and emphasizes the potential of AI-powered ECG as a disruptive diagnostic instrument (Posan & Richie, 2024).

In general, it is highlighted in the discussion that the implementation of AI-enabled ECG is preconditioned by both the demographic characteristics and psychological constructs. Although the data proved to be reliable and valid, the actual truth is that the recognition of the perceived benefits and awareness is the key lever to persuade acceptance (Minhas et al., 2024). The presented results have practical implications for healthcare policymakers, educators, and AI technology developers, indicating that awareness campaigns, professional training, and effective communication of clinical benefits can be used to hasten the process of enabling AI-enabled ECG integration into the routine cardiology practice (Han et al., 2022).

Conclusion

This work examined the awareness, perceptions, and intention to use AI-enabled electrocardiography (ECG) for predictive diagnostics. These findings validated that the data set was reliable, valid, and normally distributed, and thus it can be subjected to rigorous statistical tests. The reliability testing was very good, and the validity test (KMO and Bartlett's) was used to ascertain whether the instrument was suitable for the measurement of the underlying constructs.

The comparison within groups showed that differences according to gender and occupation are substantial, which may mean that demographic and career background influence the attitudes to AI-enabled ECG. The Chi-Square test also revealed a strong relationship between gender and the willingness to adopt, which means that when selling new technologies in health care, it is important to include everyone.

Correlation and regression were used to support the importance of awareness, knowledge, and, above all, perceived benefits as the most effective predictors of willingness to adopt AI-enabled ECG. These results illuminate the point that augmented consciousness and underlying clinical benefits, including early arrhythmia identification, enhanced risk stratification, and preventive cardiology results, will be fundamental in improving adoption.

To sum up, AI-enabled ECG is very promising as an innovative device in predictive diagnostics of cardiology. Its effective use will rely on the establishment of awareness, sharing clinical advantages, and addressing demographic gaps in perception and acceptance. Further efforts are needed in future directions to consider larger and multi-centered studies and incorporate real-world clinical validation so that AI-enabled ECG can be embraced with confidence as a standard of care in predictive cardiology.

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