Personalized Cardiovascular Therapy With Ai

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ABSTRACT

Background: AI is the trend being adopted in cardiovascular care to assist in early diagnosis, risk prediction, and tailoring of treatment. Perceptions of both the patients and the clinicians are crucial when adopting AI-based personalized cardiovascular therapy successfully.

Objective: The purpose of the study was to measure the perception, acceptance, and demographic factors affecting the willingness to adopt AI-based personalized cardiovascular therapy and to test a newly written questionnaire to measure the levels of awareness, perceived benefits, trust, and willingness to adopt AI-based personalized cardiovascular therapy.

Methods: It was a mixed-methods cross-sectional study that was carried out among 283 cardiovascular patients and 283 cardiology healthcare professionals. The questionnaire applied was a structured one with four main scales (Awareness, Benefits, Trust, Willingness) as well as an open-ended one. Cronbach's alpha was used to measure internal consistency; the Kaiser-Meyer Olkin (KMO) test and Bartlett test of Sphericity were used to assess the validity. The normality tests were conducted to examine group differences. Independent samples t-tests, one-way ANOVA, Kruskal-Wallis, Chi-square, Pearson correlation, and multiple regression were conducted to examine group differences and predictors of willingness to adopt AI.

Results: The questionnaire was found to be highly reliable (Cronbach, $\alpha = 0.82$-0.91) and strongly constructed (KMO = 0.83); so, the Bartlett p was less than 0.001. All constructs had normal distributions of data ($p > 0.05$). T reportedly have a higher awareness and perceived benefits than females ($p < 0.05$). Trust and willingness depended strongly upon education level ($p < 0.05$), and age weakly affected the willingness to adopt. Awareness, benefits, trust, and willingness were positively correlated with each other ($r = 0.66375$). The regression analysis indicated that trust was the best predictor of willingness, then benefits, awareness, and age, which explained 74 percent of the variability in intent to adopt.

Conclusion: AI-based individualized cardiovascular treatment is strongly embraced by participants, especially when they trust it and have a belief in the perceived positive outcomes. The validated questionnaire proves to be reliable and apt to measure the acceptance of AI in a cardiology context. Perspectives to enhance comprehension, sustain data confidentiality, and augment clinician support should be practiced to enhance acceptance in a variety of populations

Keywords: Artificial intelligence; personalized therapy; cardiovascular care; patient acceptance; trust; technology awareness; and healthcare innovation.

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1. INTRODUCTION

The entire globe's health killer with the most urgent health killing problem, as it takes an average of 17.9 million lives each year, and the high health care and healthcare family cost of health care is due to an economic and social need, free of a free price. The old concept of cardiovascular care providers focused more or more on the same treatment protocols obtained at a population level. It works well on the majority, though, and over-the-counter cure because it is as generic as it is, it is unlikely to reflect the minor differences of the patient in genetic or comorbid factors, lifestyle, and what occurs to the patient when receiving treatment. Consequently, the orientation towards the special member cardiovascular care, whose usage is becoming increasingly widespread, in accordance with the risk factors specific to a patient and with the clinical conditions, involves applying diagnostic and treatment procedures to individual patients (Mohammadi & Shokohyar, 2025).

This is transforming the paradigm of heart care because of the increasing availability of digital health and data analytics, and artificial intelligence (AI), which increasingly facilitate faster and more effective and patient-focused heart care. AI is the ability to transform computer machines to mimic functions that have been historically executed by human reasoning, such as pattern identification, predicting as well and informing a move. The application of AI to the cardiological field is the possibility to identify the early signs of a disease and extend the classification of risks and drugs optimization, and elaborate control of the treatment process (Khera et al., 2025).

As one example, AI algorithms will be able to process large volumes of multimodal data, such as electronic health records, imaging, wearable sensor data, and genomic data, predict poor cardiovascular events, identify tiny objects on images, and prescribe personalized treatment changes. A display of such innovations could be provided, considering the promise of the existence of the possibility of assisting patients with chronic illnesses, such as heart failure, coronary artery disease, and arrhythmias, to ease complications and advance their quality of life (Mohyeldin et al., 2025).

The advantages of the personalized cardiovascular care based on AI to populace health are also far-reaching. It does have the potential to decrease unwarranted hospital admissions, provide care at a distance in relation to susceptible populations of activity, and provide better resource distribution, with intensive care provided to individuals who are in the group at the greatest risk. Besides that, the AI-controlled application can enable a patient to be a creative, active participant in their treatment plan, suggesting certain lifestyle changes, taking pills, and reporting instances of irregular heart rates. The latter attributes are of critical importance in the low-/middle-income context, where telemedicine is already becoming an activity-level solution to the problem of geographic and fiscal distance complications due to the unavailability of cardiologists (Bednarek et al., 2025).

Opportunities History Despite this potential, there are critical issues with the far and wide use of AI-supported customized cardiovascular treatment. The issue of data privacy, in turn, will continue to pose an enormous obstacle both to patients and clinicians and to the transparency and reliability of the system. Other people have reservations about distributing personal health information via AI systems since others are afraid that the information may be misused or distributed against their wishes. A possible fear of clinical professionals is the excessive use of unreciprocated algorithms, which might be literally impossible and even unexplored, and provoke the betrayal and skepticism of patients. Equally, age, education, and prior experience with digital health technologies might condition the AI acceptance, so the need therefore arises to be aware and avoid such distinctions when constructing and implementing AI information (Shabeer et al., 2025).

The secrets to be attended to in an implementation of AI in cardiovascular medicine are to test the attitudes of the stakeholders, the predictors of implementation, and how to effectively measure and identify levels of awareness, perceived benefits, trust, and disposition to follow through with the technologies. With all these elements systematically researched, the creators of healthcare systems and technological solutions would have a chance to design communications, education, and designs to help develop up to a state of trust, equality, and rapid, secure adoption of AI-directed one-to-one treatment. The current review of literature will address this need by completing the evaluation of the perceptions and readiness of AI-based cardiovascular care and judging the reliability and validity of the newly elaborated questionnaire that should be implemented in order to accomplish this task (Srinivasan & Sharma, 2025).

2. LITERATURE REVIEW

One of the most urgent health security risks to the globe is cardiovascular diseases (CVDs) since the disease leads to colossal morbidity and mortality rates as well as exorbitant healthcare spending. Remote constitution of the traditional pattern of cardiovascular management strategies, which is based on standardized guiding clinical practice, is dominated by population-based evidence. However, these solutions frequently neglect patient-patient differences and can lead to the imbalance of medication reactivity and even ineffective care in some cases. This limited zeal has aroused the curiosity of precision medicine - personalization of treatment in which cardiovascular care will have its own peculiar aspects in patients - and in more recent periods in the application of artificial intelligence (AI) to maximize personalized cardiovascular care (Deisenhofer et al., 2025).

AI and the Transformation of Cardiovascular Care

AI is a broader term for different ways of calculation in which computers learn, find patterns, and provide predictions based on the information. In the field of cardiology, machine learning, deep learning, along natural language processing are revolutionizing the process of disease diagnosis, risk anticipation, and optimization of treatment. Algorithms of multimodal models that receive as their inputs electronic health records, laboratory parameters, imaging studies, wearable devices, etc., are superior to conventional statistical models as they predict myocardial infarction, stroke, heart failure decompensation, and arrhythmias. To point out, one might refer to convolutional neural networks (CNNs) that may be used to be trained to read echocardiograms and cardiac MRIs and perform the task with almost or even higher accuracy than a physician. Similarly, machine learning applications that train continuous data in wearable and implantable cardiac devices are capable of detecting the early signs of heart failure worsening and reacting interventively (Manoria, 2025).

Personalized Therapeutics and AI Applications

An individualized cardiovascular care attempts to go beyond the pointers in terms of generalizing and offering a perspective with regard to making access to care possible. This goal can also be supported through AI and this ways in several ways. Firstly, predictive modelling allows for stratifying patient-related risks, and makes therapeutic decisions patient-specific. Using the case of anti-hypertensive care, AI systems are trained to interpret responses to ensure that clinicians become obsessed with optimal decisions. In the case of treating heart failure, an AI-driven framework can assist in defining the subsets of phenotypes that do not respond to pharmacological and device-based therapies, to assist in personal treatments. Another AI-assisted medication compliance and lifestyle change is a predictive analytics application of AI where mobile applications and web-based coaching systems can actualize this predictive analytics to create patient-specific alerts, prompts, and behavioral cues in addition to clinical outcomes (Ortega-Martorell et al., 2025).

Procedural cardiology is another area where AI has improved. Complex interventions like transcatheter aortic valve implantation (TAVI) and coronary revascularization should be planned to be optimally combined and ultimately capable of employing algorithms, since they need imaging data and hemodynamic data (when the algorithm format receives imaging data as well as hemodynamic data). Detection of arrhythmias, targets during ablation, either remote monitoring of atrial fibrillation patients or implantable cardioverter-defibrillator patients, are such applications of AI in electrophysiology. Such developments are but a unitary progression into genuine individual care of the cardiovascular state that is guided by information, patient-focused, and installed in dynamically different change towards the health trajectory of the individual (Sharma et al., 2025).

Patient and Clinician Perspectives on AI Adoption

The electric notion of technical innovation of AI is indeed a reality, yet the COO must be embraced by patients and clinicians to successfully implement it. The concept of awareness has been elicited as the perceived benefit that constitutes a subset of the determinants that count with respect to such willingness as far as the adoption of AI-based interventions goes. The patients, who possess some knowledge about the possible advantages of AI, will then be perceived more positively by those who can help make the diagnosis correct and take the step in the right direction during the Thursday therapy individualization. It is no exception to the clinical fraternity as they must be guaranteed of the validity and safety of AI results before incorporating them into the process of their decision model (Biondi-Zoccai et al., 2025).

The former would be trust; studies have shown that mistrust towards algorithms regarding transparency, accountability, and explainability is a prominent obstacle to implementation across various health care environments. The end users will not be convinced that AI can eliminate issues about life or death without establishing its background of suggesting them. It is also a dynamic adoption issue because of the data privacy/Security. Sensitive cardiovascular health data (continuous heart rate, rhythm), vital imaging data, and genomic data should be considered as some of the sensitive data that the AI models may be able to perform better than humans at. Potential fraud and loss or misuse of information, however, is one of the most vital obstacles to patients and health practitioners. Probably, these issues could be addressed by implementing effective data governance policies, encryption policies, and political accountability to build user trust (Shah & Lodhi, 2025).

Influence of Demographic and Social Factors

Other demographic traits that are reshaping the perception of AI in healthcare include age, gender, and education. There are signs that younger adults and those with a more advanced education report a greater degree of AI system acceptance and trust and perhaps due to their greater technological awareness and a more technologically oriented work. Nevertheless, the recent research provides the information that the older generation can also become users of AI-enabled healthcare as long as the benefits are properly conveyed, and interfaces can be shaped so that they are user-friendly and user-intuitive. Inconsistent reports have also been indicated regarding the gender disparities; however, research found that males had the potential to be more optimistic and eager to apply AI technology within cardiovascular hospitals. This literature has indicated that there is a necessity to provide special education and participation strategies affected by the objective to lead the way to equal absorption among varying categories of patients (Pavunraj et al., 2025).

Measurement Tools for AI Acceptance

The focus of valid and reliable measurements that cannot be controlled by less dependable measure concepts has been established in a growing literature regarding AI acceptance in the health sector. Many scholars have generalized cardiovascular settings through the use of the current-state modes of technology acceptance, like the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). No instruments have been tested in particular to use in individual cars of heart treatment, unfortunately. The set of stable measurement instruments can capitalize on research and practice that is able to measure two or more dimensions of awareness, perceived usefulness, trust, and willingness. The authentication of these tools would be the assurance to use adequate and useful information in designing interventions, which would bring us the AI (Croon et al., 2025).

Research Gaps and Rationale for the Present Study

So, it is still a gradual process, but there are information gaps. There is a paucity of literature exploring a mix of trust alongside the expertise and perceived benefit to foretell eagerness to use AI within cardiovascular care, particularly in low and middle-income settings where optimizing the maximum amount of resources is strongly pertinent. Moreover, not all the research studies present the rigorous psychometric assessment of the instruments involved in the measurement of AI perceptions, which restricts the externalization of the findings of such studies. This will be important in eliminating such gaps and assist in the field of cardiology, where AI can be used to the advantage of patients and maximize safety, by developing patient plans (Babu et al., 2025).

The current literature is shown by the fact that it is included in the field of the current study, where it constitutes a fully empowering cardiovascular therapy awareness, preceded by its virtues, trust, and willingness to be used, its questionnaire. The study will provide effective recommendations to encourage the use of AI technologies to foster equal and valid uptake, along with causing an increase in cardiovascular outcomes by implementing the utility of the great predictors, simultaneously taking into account how constructs of the great may come into conflict with others (Nechita et al., 2025).

3. RESEARCH METHODOLOGY

Study Design

The paper is a mixed-method, cross-sectional one, the purpose of which is the investigation of the use of Artificial Intelligence (AI) as a solution in personalized cardiovascular care. The rationale of the mixed approach adoption is that it will allow incorporating both quantitative data to be obtained in the form of structured questionnaires and qualitative information to be collected in the form of open-ended questions. This type of design will allow the study to not only quantify the level of awareness of AI and trust and adoption of AI by people who have cardiovascular conditions, but will also allow for to quantification of more refined views and concerns that would not necessarily be quantifiable (Haq et al., 2021).

Study Population and Sampling

The patient ego (adult patients with cardiovascular disease (CVD)) and patient health care professional (physicians, nurses, and allied health staff members who have reported some knowledge of digital health tools) will constitute the study population. The participants will be sampled using tertiary care hospitals and special clinics on the websites of cardiology and cardiovascular support. A purposive sampling policy will also be used, and this will ensure a diverse sample in terms of age, men, and women, education levels, and previous experience with AI-based health technologies. The recruited participants will be 283 so as to achieve the desired statistical power and reliability to carry out the target analyses (Mohsen et al., 2023).

Data Collection Instrument

As some of the pleiades, a structured questionnaire specially developed as a result of the current study will be adopted as the primary data gathering means. The questionnaire can be subdivided into six domains: demographic data, AI awareness and knowledge in cardiovascular care; perceived benefits of AI-driven personalized therapy, trust and concerns about AI, willingness to implement AI-driven personalized therapy, as well as the open-ended questions. These perceptions and attitudes will be assessed using a 5-point Likert scale (Strongly Disagree to Strongly Agree) on questions included in the key sections. The questionnaire shall, in a manner that will ensure the validity, undergo content analysis by a panel comprising 20 cardiology and digital health experts and be piloted by 20 people to help in clarifying the questionnaire and developing this in a manner that is culturally acceptable. Cronbach's alpha is going to be used to verify the internal consistency reliability, and the recommended real number here is 0.7 (Al-Maini et al., 2023).

Data Collection Procedure

With the permission, we will contact the participants to complete the Questionnaire online with the aid of definite forms or the already filled Questionnaire, which we will distribute in the clinical waiting rooms. The respondents will be informed about the purpose of the study and given informed consent, with the assurance that their names will not be released. The use of an estimate at four weeks would be adequate when gathering the data to facilitate the economic sample size and coverage (Sun et al., 2023).

Data Management and Analysis

Digital data obtained will be assessed with the help of SPSS or R. Specifically, demographic characteristics and overall perception scores will be summarized with the help of descriptive statistics: i.e., frequencies, percentages, means, and standard deviations. Normal distribution laws, like the Shapiro-Wilk test, will be conducted. Cronbach's alpha, KMO, and Bartlett test will help ascertain the reliability of the instrument and its suitability for district analysis. Comparatively related analyses will be determined using the Independent Tests, One-way ANOVA, Kruskal-Wallis test, and Chi-square Test will be introduced to determine the difference in analyses concerning the demographical groups. Correlations and multiple regression analyses will be used to predict the particularities of the investigation as per the readiness of participants to use the AI-powered personalized therapy. Thematic content analysis will be used to analyze open-ended types of qualitative questions to determine common issues and suggestions (Singh et al., 2024).

Ethical Considerations

In this study, there is confidentiality and protection of data, and voluntary participation. All the personal identifiers will not be made. The students are allowed to abandon the process whenever they feel. The information will be electronic, and it will be encrypted and stored (Khera et al., 2024).

Data Analysis

Table 1: Normality Test

Scale	Shapiro–Wilk p-value	Normality Status
Awareness	0.128	Normal Distribution
Benefits	0.214	Normal Distribution
Trust	0.165	Normal Distribution
Willingness	0.239	Normal Distribution

Normality Test

Table 1 shows the normality test of the data. When analyzing using the normal test, it was found that the composite scores of all four variables, Awareness, Perceived Benefits, Trust and Concerns, and Willingness to Adopt AI-driven cardiovascular therapy, rejected the odds ratio at the normal distribution. The p-values of the Shapiro-Wilk test of the different scales were above 0.05, and the data were more or less normally distributed. Such an outcome warrants the use of a parametric statistics approach towards unpackaged statistics (Mohsin et al., 2023).

Table 2: Reliability Test

Scale	Cronbach's Alpha	Reliability Interpretation
Awareness	0.82	Excellent Reliability
Benefits	0.88	Excellent Reliability

Trust	**0.91**	**Excellent Reliability**
Willingness	**0.85**	**Excellent Reliability**

Reliability Test

Table 2 shows the reliability analysis of the data. All constructs also had excellent internal consistency depicted in the reliability analysis. The Cronbach Alpha values were: Awareness (0.82), Benefits (0.88), Trust (0.91), and Will Being (0.85). All values above the required number of 0.70 indicate that the items of the questionnaire can be considered rather trustworthy in testing the constructs under investigation (Visco et al., 2021).

Table 3: Validity Test — KMO & Bartlett's

Test	Value	Interpretation
Kaiser–Meyer–Olkin (KMO)	0.83	Sampling Adequacy — Meritorious
Bartlett's Test	$\chi^2$865.47	$p < 0.001$ — Significant

Validity Test

Table 3 shows the validity test of the data Kaiser-Meyer-Olkin (KMO) test and Bartlett test of sphericity were developed to evaluate usual construct validity. The KMO equal to 0.83 was a sign of satisfactory meritorious sampling, as well as the Test of Bartlett elicited very significant values ($p < 0.001$). These findings confirm the hypothesis that the element of the correlation matrix could be employed to uncover a factor analysis and that the items do sufficiently capture the paradigm of concepts in conjunction with the application of AI in cardiovascular treatment (Mathur et al., 2020).

Table 4: Group Comparison Results

Test / Scale	Comparison Groups	Test Statistic	p-value	Interpretation
Independent Samples t-test	Gender (Male vs Female) — Awareness	$t = 2.31$	0.022	Significant difference: males have higher awareness
	Gender (Male vs Female) — Benefits	$t = 2.85$	0.005	Significant difference; males higher benefits perception
One-way ANOVA	Education Levels — Trust	$F = 3.92$	0.009	Significant difference across education levels
	Education Levels — Willingness	$F = 4.31$	0.006	Significant difference across education levels
Kruskal–Wallis	Age Groups — Awareness	$H = 11.27$	0.024	Significant differences across age categories
	Age Groups — Benefits	$H = 10.82$	0.029	Significant differences across age categories
Chi-Square	Gender × AI Use	$\chi^2 = 8.54$	0.014	Significant association; males are more AI users
	Education × AI Use	$\chi^2 = 13.67$	0.031	Significant association; higher education → more AI use

4. GROUP COMPARISON FINDINGS

Gender-Based Differences

Table 4 shows the Group Comparison of the data. It was observed that the independent samples t-tests showed a significant mean of Reing Awareness and Perceived Benefits when applied to male respondents as compared to the respondents of the female gender ($p < 0.05$). This suggests that perhaps now, men are less confident or optimistic about the AI technologies in cardiovascular care (Blasiak et al., 2020).

Education-Based Differences

ANOVA- One Way found statistically significant differences among education levels in the case of Trust and Willingness to adopt AI-driven therapy($p < 0.05$). The respondents who were better educated were more confident in AI and showed more interest in implementing AI-based therapy in their practice (Romiti et al., 2020).

Age-Based Differences

Kruskal-Wallis tests (nonparametric) were used to test the significance of the difference in Awareness and Perceived Benefits of the groups using age ($p < 0.05$). Such findings imply that the perception of AI technology is age-specific in that the respondents of younger age and the respondents of older age hold divergent perceptions and preferences towards the technology (Krittanawong et al., 2022).

Associations with AI Use

The chi-square results indicated that demographics were related to the usage of AI health tools with significance in the past. The higher level of education and the male respondents who used AI at a higher rate indicated that there are likely demographic factors predicting early technological usage (Schork, 2019).

Table 5: Pearson Correlation Matrix

Scale	Awareness	Benefits	Trust	Willingness
Awareness	1.00	0.72	0.69	0.66
Benefits	0.72	1.00	0.74	0.70
Trust	0.69	0.74	1.00	0.75
Willingness	0.66	0.70	0.75	1.00

Correlation Analysis

Table 5 shows the correlation analysis of the data. All constructs were strongly positively correlated in the Pearson matrix of correlation. Greater Awareness and recognition of benefits also correlated more with his positive trust to adopt AI therapy (r values > 0.65). To this, the knowledge and perceived usefulness stand out as some of the dissimilar influential factors in acceptance (Bertsimas et al., 2020).

Table 6: Multiple Regression

Predictor	Coefficient (β)	t-value	p-value
Constant	1.12	4.25	<0.001
Awareness	+0.28	5.42	<0.001
Benefits	+0.31	6.03	<0.001
Trust	+0.35	6.88	<0.001
Age	+0.12	2.57	0.011

Regression Analysis

Table 6 shows the regression analysis of the data. Moving Willingness to adopt AI-driven cardiovascular therapy emerged as an important variable with the ability to explain 74 percent of the variance ($R^2 = 0.74$) when estimated using the multiple regression model. Trust to Benefits and Awareness emerged as the farthest biggest positive foreboding turn out was Trust. Age, too, was rather but materially dependent. Based on these observations, it can be assumed that promoting trust and focusing on the practical benefits of AI have the potential to boost the readiness to receive the individualized AI treatment among users immensely (Kagiyama et al., 2019).

Figure 1 — Normality Test (Shapiro–Wilk p-values)

Figure 1 shows the normality test of the data. Our figure of normality indicates that the p-values of Awareness (0.128), Benefits (0.214) and Trust (0.165), and Willingness (0.239) are all above the 0.05 point. This indicates that the data sets are reasonably normally distributed, hence can be used in analogous tests such as t-tests, ANOVA, and Pearson correlation tests (Addissouky et al., 2024).

Figure 2 — Reliability (Cronbach's Alpha)

Figure 2 shows the reliability analysis of the data. This bar graph shows that all four scales (Awareness, Benefits, Trust, Willingness) achieved a Cronbach alpha (0.82 to 0.91) and are significantly higher than (0.70) required. The outcome is the red dashed line, which is the minimum acceptable level of reliability. All the above scales exceed this standard, which substantiates the fact that this questionnaire demonstrates high internal consistency and a set of items appeals to the particular construct (Di Renzo et al., 2020).

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

Figure 3 shows the validity test of the data. This value shows that the KMO value equals 0.83, well surpassing the correct range of 0.6, and therefore, to factor-analyze the sample size and correlations are sufficient to analyze it appropriately. The Test of Sphericity with Bartlett has a high value (2 = 865.47, p = 0.001), which indicates that the matrix of correlation is not the product of the coincidence (Infante et al., 2020).

Figure 4 — Group Comparisons (t-test, ANOVA, Chi-square)

Figure 4 shows the Group Comparisons of the data. The results in the combined chart are the following on the group level (Thangaraj et al., 2024):

According to the t-test (left panel), males significantly outranked females in Awareness and Benefits, indicating statistically significant differences (p under 0.05) in that males were modestly aware and positive about AI in heart care (Gala et al., 2024).

Increase in Trust and Willingness by the education level: The ANOVA (middle panel) explicitly demonstrates a definite enhancement of the level of Trust and Willingness with higher levels of education understandably signify improved trust and acceptance of AI ($p < 0.05$) (Infante et al., 2021).

The Chi-square (right panel) shows that a higher number of men had used AI in the past compared to women; the level of education was also a big influencing factor on the use of AI (Sufian et al., 2024).

Figure 5 — Pearson Correlation Matrix

Figure 5 shows the correlation matrix of the data. According to the heatmap, it is only exhibited by the fact that the correlation among all constructs is very strong and positive. Benefits (R= 0.72) and Trust (R= 0.69) are highly related to Awareness, and the three have significant Awareness (R= 0.66- 0.75). This proves that people who are smarter on the effects of the AI and more beneficial are also more reliable and eager to use AI-based cardiovascular treatment (Armoundas et al., 2024).

Figure 6 — Regression Coefficients

Figure 6 shows the regression analysis of the data. The regression bar chart suggests that Willingness to adopt AI therapy was significantly positively influenced by Trust, Benefits, and Awareness. Trust and Benefits, and Awareness prove to be the most effective predictors. The positive, small but significant effect of age is present as well. The general regression model provides a sufficient explanation of 74 percent of willfulness (R 2 = 0.74), thereby indicating that these factors exhibit general outstanding strong elucidators of adoption (Yang, 2024).

5. DISCUSSION

The paper has examined artificial intelligence (AI) perceptions and acceptance when used in personalized cardiovascular therapy, and also evaluated the psychometric level of a questionnaire created recently. In total, one can say that this instrument was of high quality in terms of measurement, and internal consistency ranks well, and validity indices are high. The alpha of all scales exceeded the generally acceptable threshold of 0.70, which certified them as working items in their specific constructs of awareness, perceived benefits, trust, and willingness to use AI-driven care. Automatic Kaiser-Meyer-Olkin (KMO) value as well as high Bartlett's Test indicated that the questionnaire's latent structure was good to factor-analyze and provide a sound, plausible basis for analyzing attitude towards AI in cardiovascular health (Xiaotong et al., 2023).

At the level of the results, the positive acceptance and readiness to accept AI-based personalised therapy among the participants of the research were observed. The interrelation of these constructs is reflected in a positive and significant relation between awareness, perceived benefits, trust, and willingness. To be more exact, the population that better understood the AI technologies and better visualized what value it can provide to them was more likely to believe in the AI systems and show a desire to integrate them into their cardiovascular treatments. It corroborates previous sources that suggest that knowledge and perceived usefulness are determinants of the digital health adoption (Arikhad et al., 2024).

Demographic analyses of significant differences were made. When males were contacted with females, it turned out that male participants were sort of more aware of all that AI can provide, and that the female participants are capable of sensing that, as well. It may be a sign of variation in the extent to which people were exposed to technology or were confident about using digital devices, which was equally evident in other studies in the field of healthcare technology. Educational attainment was another factor; those with a higher education received a very high rate of trust and willingness to adopt AI therapy. This means that tertiary education can contribute to increasing expertise about more complex technologies and diminishing the anxiety related to their insecurity and unreliability. Age was repeatedly significant but in a less decisive supportive effect on willingness to adopt AI, and it revealed that younger population sets are not the sole age group prepared to adopt AI solutions, and the elderly may similarly be prepared, provided that effective communication of advantages and security (Johnson et al., 2021).

The regression analysis also pointed out that trust is a major element that influences the take-up of AI. Trust and then perceived benefits and awareness were the most predictive ones. It is important to consider the significance of how to create AI systems in a transparent, safe, and clinician-approved way. By letting health users believe that the advice its systems produce is sound, their health information is safe, and the technology augments, rather than supplants, the body of knowledge of its medical expert, it stands a chance of being adopted into medical care (Tokodi et al., 2020).

In a practical sense, these findings have an application to the successful implementation of AI in cardiovascular therapy. Firstly, it should put more focus on retraining patients and clinic staff again to foster the awareness level and explain the specific benefits of AI-based interventions, such as having the chance to anticipate threats more effectively, providing particular treatment guidance, and utilizing remote tracking. Second, it is important to speak about the problem of privacy, safety, explain it, and establish trust. Fear could be reduced through effective information about the policies of data security and control over the issue. Finally, it would need particular attempts to service demographic tabs with reduced table of digital construction or comfort, which might be individuals with an informal education, necessitating prior experience of digital health (Taherdoost & Ghofrani, 2024).

Despite the useful lessons the current research has to offer, a few limitations must be mentioned. Sampling: The cross-sectional research design does not provide the option of causal sampling, and the sample, though too heterogeneous, might not fully represent all patients with cardiovascular disease and their delivery system. The longitudinal design in future studies might allow tracking the alteration of attitude and adoption behaviour due to the increasing ubiquity and integration of AI-based cardiovascular interventions in clinical environments (Oikonomou & Khera, 2023).

6. CONCLUSION

As it emerges in this paper, AI is 80 percent likely to revolutionize the cardiovascular care provision, as it allows personalized care that responds to the requirements of a specific patient. The self-constructed questionnaire on the level of awareness, perceived benefits, trust, and willingness to use AI-driven hemi-cardiovascular therapy proved to be psychometrically proper, highly reliable, and valid. The findings demonstrated a significant and positive association of such primary constructs with the rest of them, and that trust is the most urgent factor that should be obtained and present to give a prediction that involves the willingness to adopt AI solutions, and consequently, to the perceived benefits and familiarity.

The contribution of demographic research has defined that both education and the age of women play a role in perceptions and acceptance toward the use of AI, which is necessary to factor into the implementation strategies. The people with past exposure also had a higher exposure rate compared to repeatedly exposed educated people, although concrete educational and interests can lower the unwillingness rate of the people who were not exposed before.

To maintain trust and transparency, as was also mentioned in the results, one should initially work on integrating artificial intelligence into the treatment chain for patients of the cardiovascular system. Healthcare development facilities and providers are also encouraged to concentrate on the development of safe and explainable AI technology with privacy enforcement, and to help healthcare practitioners understand the advantages of artificial intelligence. Patients and clinicians: Intensification can also be achieved, and patient-centered programs can be achieved through education that can be provided to clinicians and patients, so that they are guaranteed to be absorbed by populations.

Among other factors, an honest measurement tool and its psychological, demographic motivation to believe in AI can be validated and serve as one of the anchor points of future research and policy formulations. It provides the corresponding recommendations to the health systems, the innovators, and the decision makers that could theoretically catalyze the action of the AI-driven individualized cardiovascular treatment that would ultimately produce higher patient rates and more efficiently delivered health care.

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