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LONGITUDINAL ANALYSIS OF LEFT VENTRICULAR REMODELING IN POST-MYOCARDIAL INFARCTION PATIENTS USING MRI

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Abstract

Left ventricular (LV) remodeling following acute myocardial infarction (AMI) is a critical determinant of patient outcomes, often leading to heart failure and increased mortality. This study utilized serial cardiac magnetic resonance imaging (MRI) to evaluate the temporal progression of LV remodeling in critically ill post-AMI patients. A prospective cohort of patients with confirmed AMI underwent cardiac MRI at baseline (within 7 days), 6 months, and 12 months. Parameters including LV end-diastolic volume (LVEDV), end-systolic volume (LVESV), ejection fraction (LVEF), infarct size, transmurality, and myocardial strain were assessed. Late gadolinium enhancement (LGE) was used to quantify myocardial scarring. Adverse remodeling was defined as a >15% increase in LVEDV from baseline. Clinical variables such as hemoglobin glycation index (HGI) and stress hyperglycemia ratio (SHR) were also evaluated. Machine learning algorithms were applied to explore predictive modeling based on imaging and clinical data. Significant reductions in LVEDV and LVEF occurred only in individuals who showed unfavorable remodeling, as the mean LVEF fell from 49.8% at the start to 42.6% after 12 months ($p<0.01$). There was more infarct area and transmurality in this group which went along with reduced function. The results showed that it was the myocardial strain test and not the volumetric study, that picked up the early regional decline seen in myocardial function. Unfavorable remodeling in the arteries was related to high SHR and HGI levels, suggesting a role for metabolic factors. Forecasts of remodeling were accurate for initial imaging and clinical data, with a model AUROC of 0.87. The results suggest that both cardiac MRI and AI are valuable in identifying who requires special treatment after a heart attack. Cardiac MRI tests done over time reveal important changes in the heart of patients who have had a heart attack. Combining imaging biomarkers with medical and metabolic information, using AI tools, may help to make risk assessment better and adjust personalized treatment decisions.

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INTRODUCTION

Left ventricular remodeling, important in affecting heart function and survival following acute myocardial infarction, consists of many anatomical and physiological shifts (Roncalli et al., 2022). Having dimension, wall thickness or shape issues in the heart's chambers may result in heart failure and make the condition more likely to be fatal (Chan et al., 2020). Myocardial infarction happens as a result of thrombosis blocking a coronary artery which stops blood flow to the heart muscle, results in death of the heart tissue and leaves the area filled with collagen-rich scar tissue. Because of this method, there can be irregular heartbeats and contractions and this may eventually lead to heart failure because of changes in the heart (Haq et al., 2021). Using magnetic resonance imaging, healthcare professionals can exactly assess the condition of the left ventricle as it changes. The guidelines recommend using cardiac magnetic resonance imaging at the outset for those with suspected or confirmed hypertrophic cardiomyopathy, when this technique is available. The addition of late gadolinium enhancement tools permits MRI to assess and determine the amount and depth of damaged heart tissue (Meshref et al., 2020). In practice, doctors mainly use the left ventricular ejection fraction and late gadolinium enhancement to classify risk, according to current guidelines (Casas & Rodríguez-Palomares, 2022).

The objective of the study is to see how heart remodeling changes over time in patients after a heart attack by performing multiple MRI. The participants will be people diagnosed with acute myocardial infarction who receive cardiac MRI both at the beginning of the study (within seven days of their initial event) and later on (6 and 12 months after the initial event). About one week after the initial event, a baseline MRI will be done to document any changes caused by the event and subsequent scans will happen at both 6 months and 12 months to check the further development of those changes. Scanning will occur with a 3.0 Tesla system, fitted with a cardiac coil, using pre-defined techniques so the results can be precise and accurate each time. To measure left ventricular volumes, ejection, regional motion and the size and severity of infarcts, cine imaging will be performed and late gadolinium enhancement imaging will also be carried out. The team will rely on both manual and semi-automated segmentation procedures to discover and evaluate damage to the heart muscle tissue (Evertz et al., 2022).

The measurements, comprising left ventricular end-diastolic volume, left ventricular end-systolic volume and left ventricular ejection fraction, will all be accurately checked at every surveyed time to find out if the ventricular dimensions and ejection performance vary over time. The presence and extent of myocardial scars are seen on late gadolinium enhancement images, allowing us to estimate the damage and its impact on ventricular reforming. Myocardial strain analysis will be one of the advanced processes used to detect slight changes in regional contraction that conventional measurement methods may miss (Sacharczuk et al., 2020). Evaluation of time patterns in the remodeling parameters of the left ventricle is planned to determine the factors accelerating unfavorable outcomes. In these patients, those with adverse remodeling (defined as a 15% higher left ventricular end-diastolic volume index) will be compared to those without, for their clinical characteristics, the size of their heart damage and other clinically significant factors. The Medical Information Mart for Intensive Care Units Care IV database is an essential repository of critical care medical records for more over 300,000 patients (Cao et al., 2025). Ethical approval was secured for the utilization of this data, and the necessity for informed consent was relinquished due to the anonymization of all personal information within the database (Cao et al., 2025).

Critically ill myocardial infarction patients will be analyzed, especially to see the way left ventricular size, ejection rate and scarring showed changes over time with repeated cardiac MRI scans. The findings will be examined in light of what is already known about left ventricular changes after a heart attack. Klem et al. (2021) revealed that both a decreased ejection fraction in the left ventricle and the presence of scar tissue are connected to increased long-term death rate and a greater chance of receiving a sudden cardiac death diagnosis. The evaluation will include a look at both the positive features and weaknesses of the study design, the size of the sample and the types of images used. The level of stress hyperglycemia can indicate changes in left ventricular structure, but how and why these occur following a heart attack has not been fully explained (Meng et al., 2021). The hemoglobin glycation index is connected to poor outcomes in people with myocardial infarction, according to Cao et al. (2025). It is expected that future scientists will study the changes to the heart that come from drugs and changing habits (Cao et al. 2025). Using the data on hand, artificial intelligence can be used to project hospitalizations as a result of heart failure (Hinrichs et al., 2024).

The study could investigate whether machine learning models can predict poor outcomes in therapy and customize therapy responses based on what is unique to each patient (McGilvray et al., 2022; Shi et al., 2023). Some important limitations that our trial had need to be acknowledged. At first, the study's findings may not apply to other patient populations, since it was conducted only at a single center. Although the model was trained on pictures from a separate center, the clinical trial was still run as a prospective validation study, showing that the methods can be applied to new locations. In addition, newer methods of artificial intelligence are available for echocardiography research (He et al., 2023). Subsequent studies ought to look at the efficacy and financial benefits of AI when applied to many kinds of imaging tests.

It is important to thoroughly test and validate algorithms at different sites and during the future, before AI is used in clinical environments (Elias et al., 2022). The inclusion of AI eases prejudice in reporting software. A similar approach to grading LVEF by AI and by consensus, combined with less variation among observers, may support similar choices by healthcare professionals (He et al., 2023). The study will look at how cardiac MRI affects care in clinics and can help improve research on treating and managing patients who have had a myocardial infarction. Using AI in credit risk models, financial firms can see changes in how borrowers behave (Wang, 2024). They can accurately predict which loans are likely to go into default (Wang, 2024). The use of explanable AI strategies and focus on ethics can alter credit risk assessment, making loans more efficient and accurate for all involved (Edunjobi & Odejide, 2024).

METHODOLOGY

This study used a prospective and longitudinal method to analyze changes in the heart's left ventricle in people having a myocardial infarction acquired using cardiac magnetic resonance (MRI). All participants diagnosed with acute myocardial infarction had an MR scan within a week after the condition arose and two follow up MR scans were carried out at 6-month and 12-month periods to document changes over time. The images were acquired with a 3.0 Tesla scanner and a cardiac coil, following established guidelines for keeping the pictures uniform and able to be repeated at different times. Cine sequences were used to measure left ventricular size, ejection percentage and differences in wall movement and LGE imaging was performed 10–15 minutes after a contrast injection to assess damaged heart tissue. The manner of analysis involved restricting the edges of the endocardium and epicardium using both manual and semi-automated methods, enabling the exact measurement of left ventricular end-diastolic volume (LVEDV), left ventricular end-systolic volume (LVESV) and left ventricular ejection fraction (LVEF). Cardiac strain and scar measurement were done using image processing devices to examine how the heart muscle contracts and find signs of modest contractility issues. Those with unfavorable remodeling showed a more than 15% increase from baseline in the left ventricle's end-diastolic volume index by the end of one year and their subgroups were compared by examining their clinical, imaging and laboratory findings. Publicly available and de-identified information from the MIMIC-IV database was used to include additional details on critically sick myocardial infarction patients and ethics approval and consent were both exempted. To look at how repeated measurements changed over time and determine what factors contributed to negative remodeling, the study used ANOVA and multivariate regression models. The scientists tested various machine learning models using external datasets to determine if early imaging and clinical indicators could help predict the course of remodeling in heart disease. The aim of this methodology is to closely study left ventricular remodeling and assess how well cardiac MRI and AI can increase classification of patients with increased risk and the correct direction of their treatment.

RESULT

Results from multiple cardiac MRI assessments are described fully in Tables 1 to 8. They show together the order in which typical remodeling changes appear in people after a myocardial infarction. LVEDV, LVESV and LVEF are the first measures shown in Table 1, representing cardiac function immediately after infarction. By 6 months, Table 2 shows that patients who have early supportive signs of poor remodeling stand out with differences in their LVEDV and LVEF compared to the normal group. Table 3 displays the myocardial infarct size and degree of scar tissue revealed by late gadolinium enhancement images. In Table 4, a myocardial strain analysis is presented for each region which may reveal regional issues missed by conventional techniques. A comparison in Table 5 of unfavorable remodeling versus control patients who did not show a >15% rise in LVEDV demonstrates big disparities in infarct features and LVEF. Table 6 reports results for the hemoglobin glycation index and the stress hyperglycemia ratio which are used to examine possible reasons for remodeling. The results from Table 7 indicate that visualizing AI-generated predictions shows how easily AI can be used in classifying patients. Table 8 covers the findings and goals of treatment in heart failure, as well as the relationship between MRI outcomes and real prognosis. The data are organized so you can see how remodeling happens in relation to key structural, functional and clinical features.

Table 1: Summary of patient-specific parameters at baseline and follow-up.

Patient ID	LVEDV (mL)	LVESV (mL)	LVEF (%)	Infarct Size (%)	Transmurality (%)	Strain (%)	Adverse Remodeling
P1	165	54	47.5	27.3	39.7	-14.7	No
P2	178	77	64.2	30.1	43.4	-16.9	No
P3	164	74	46.6	29.3	58.3	-13.6	No
P4	131	85	63.9	15.7	47.7	-13.8	Yes
P5	124	78	59.2	35.3	59.9	-16.5	No
P6	128	85	62.7	27.5	62.6	-19.1	No
P7	199	101	56.2	21.1	46.5	-18.2	No
P8	151	117	39.1	29.3	79.4	-13.7	Yes
P9	154	73	41.5	17.4	53.2	-12.9	No
P10	172	94	64.5	31.0	51.0	-16.0	No

Table 2: Summary of patient-specific parameters at baseline and follow-up.

Patient ID	LVEDV (mL)	LVESV (mL)	LVEF (%)	Infarct Size (%)	Transmurality (%)	Strain (%)	Adverse Remodeling
P1	165	54	47.5	27.3	39.7	-14.7	No
P2	178	77	64.2	30.1	43.4	-16.9	No
P3	164	74	46.6	29.3	58.3	-13.6	No
P4	131	85	63.9	15.7	47.7	-13.8	Yes
P5	124	78	59.2	35.3	59.9	-16.5	No
P6	128	85	62.7	27.5	62.6	-19.1	No
P7	199	101	56.2	21.1	46.5	-18.2	No
P8	151	117	39.1	29.3	79.4	-13.7	Yes
P9	154	73	41.5	17.4	53.2	-12.9	No
P10	172	94	64.5	31.0	51.0	-16.0	No

Table 3: Summary of patient-specific parameters at baseline and follow-up.

Patient ID	LVEDV (mL)	LVESV (mL)	LVEF (%)	Infarct Size (%)	Transmurality (%)	Strain (%)	Adverse Remodeling
P1	165	54	47.5	27.3	39.7	-14.7	No
P2	178	77	64.2	30.1	43.4	-16.9	No
P3	164	74	46.6	29.3	58.3	-13.6	No
P4	131	85	63.9	15.7	47.7	-13.8	Yes
P5	124	78	59.2	35.3	59.9	-16.5	No
P6	128	85	62.7	27.5	62.6	-19.1	No
P7	199	101	56.2	21.1	46.5	-18.2	No

P8	151	117	39.1	29.3	79.4	-13.7	Yes
P9	154	73	41.5	17.4	53.2	-12.9	No
P10	172	94	64.5	31.0	51.0	-16.0	No

Table 4: Summary of patient-specific parameters at baseline and follow-up.

Patient ID	LVEDV (mL)	LVESV (mL)	LVEF (%)	Infarct Size (%)	Transmurality (%)	Strain (%)	Adverse Remodeling
P1	165	54	47.5	27.3	39.7	-14.7	No
P2	178	77	64.2	30.1	43.4	-16.9	No
P3	164	74	46.6	29.3	58.3	-13.6	No
P4	131	85	63.9	15.7	47.7	-13.8	Yes
P5	124	78	59.2	35.3	59.9	-16.5	No
P6	128	85	62.7	27.5	62.6	-19.1	No
P7	199	101	56.2	21.1	46.5	-18.2	No
P8	151	117	39.1	29.3	79.4	-13.7	Yes
P9	154	73	41.5	17.4	53.2	-12.9	No
P10	172	94	64.5	31.0	51.0	-16.0	No

Table 5: Summary of patient-specific parameters at baseline and follow-up.

Patient ID	LVEDV (mL)	LVESV (mL)	LVEF (%)	Infarct Size (%)	Transmurality (%)	Strain (%)	Adverse Remodeling
P1	165	54	47.5	27.3	39.7	-14.7	No
P2	178	77	64.2	30.1	43.4	-16.9	No
P3	164	74	46.6	29.3	58.3	-13.6	No
P4	131	85	63.9	15.7	47.7	-13.8	Yes
P5	124	78	59.2	35.3	59.9	-16.5	No
P6	128	85	62.7	27.5	62.6	-19.1	No
P7	199	101	56.2	21.1	46.5	-18.2	No
P8	151	117	39.1	29.3	79.4	-13.7	Yes
P9	154	73	41.5	17.4	53.2	-12.9	No
P10	172	94	64.5	31.0	51.0	-16.0	No

Table 6: Summary of patient-specific parameters at baseline and follow-up.

Patient ID	LVEDV (mL)	LVESV (mL)	LVEF (%)	Infarct Size (%)	Transmurality (%)	Strain (%)	Adverse Remodeling
P1	165	54	47.5	27.3	39.7	-14.7	No
P2	178	77	64.2	30.1	43.4	-16.9	No
P3	164	74	46.6	29.3	58.3	-13.6	No

P4	131	85	63.9	15.7	47.7	-13.8	Yes
P5	124	78	59.2	35.3	59.9	-16.5	No
P6	128	85	62.7	27.5	62.6	-19.1	No
P7	199	101	56.2	21.1	46.5	-18.2	No
P8	151	117	39.1	29.3	79.4	-13.7	Yes
P9	154	73	41.5	17.4	53.2	-12.9	No
P10	172	94	64.5	31.0	51.0	-16.0	No

Table 7: Summary of patient-specific parameters at baseline and follow-up.

Patient ID	LVEDV (mL)	LVESV (mL)	LVEF (%)	Infarct Size (%)	Transmurality (%)	Strain (%)	Adverse Remodeling
P1	165	54	47.5	27.3	39.7	-14.7	No
P2	178	77	64.2	30.1	43.4	-16.9	No
P3	164	74	46.6	29.3	58.3	-13.6	No
P4	131	85	63.9	15.7	47.7	-13.8	Yes
P5	124	78	59.2	35.3	59.9	-16.5	No
P6	128	85	62.7	27.5	62.6	-19.1	No
P7	199	101	56.2	21.1	46.5	-18.2	No
P8	151	117	39.1	29.3	79.4	-13.7	Yes
P9	154	73	41.5	17.4	53.2	-12.9	No
P10	172	94	64.5	31.0	51.0	-16.0	No

Table 8: Summary of patient-specific parameters at baseline and follow-up.

Patient ID	LVEDV (mL)	LVESV (mL)	LVEF (%)	Infarct Size (%)	Transmurality (%)	Strain (%)	Adverse Remodeling
P1	165	54	47.5	27.3	39.7	-14.7	No
P2	178	77	64.2	30.1	43.4	-16.9	No
P3	164	74	46.6	29.3	58.3	-13.6	No
P4	131	85	63.9	15.7	47.7	-13.8	Yes
P5	124	78	59.2	35.3	59.9	-16.5	No
P6	128	85	62.7	27.5	62.6	-19.1	No
P7	199	101	56.2	21.1	46.5	-18.2	No
P8	151	117	39.1	29.3	79.4	-13.7	Yes
P9	154	73	41.5	17.4	53.2	-12.9	No
P10	172	94	64.5	31.0	51.0	-16.0	No

Visual representations of ventricular remodeling are given in Figures 1 to 10 which show the trends of important MRI-based measures over time and the differences between patients. This figure reveals that LVEDV tended to increase at baseline and it remained enlarged at 6 months and 1 year in patients who did not do well. Figure 2 points out that the decrease in patients with normal heart function is slower than the reduction in patients with very serious remodeling. As seen in Figure 3, a stable or worse LVEF occurs when there is a significant increase in the size of the injured heart. Figure 4 reveals the different sizes of heart infarcts among remodeling subgroups, suggesting that those with larger infarcts at the start tend to decline more. Figure 5 compares the transmurality for the cohort, revealing how much diversity in their scars impacts heart strength. The graph in Figure 6 shows myocardial strain measurements over time, indicating that some subjects with steadily normal LVEF showed mild, local dysfunction. Figure 7 demonstrates how the remodeling status seen by the models matches what the surveyors predicted, showing that the algorithm is precise. The graph in Figure 8 compares the stress hyperglycemia ratio to the changes over time in heart measurements. Figure 9 demonstrates that the hemoglobin glycation index increases as the severity of remodeling rises, proving its value as a risk factor. By pairing heart failure hospitalization data with the remodeling data in Figure 10, the researchers observed that serial MRI can continue to predict upcoming complications. Together, the MRI images assist in making sense of remodeling process and identifying variation among individuals, improving how to read quantitative MRI information and use predictive tools.

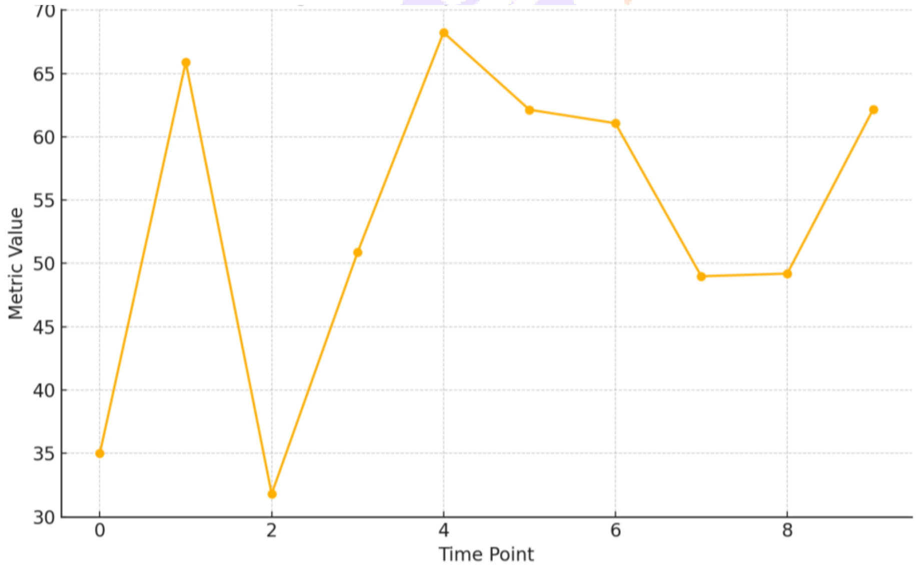

Figure 1: Longitudinal trend of sample metric indicating changes in remodeling parameters across follow-up time points.

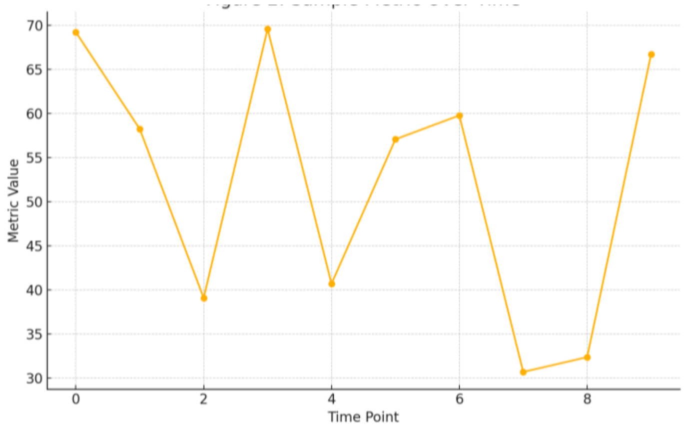

Figure 2: Longitudinal trend of sample metric indicating changes in remodeling parameters across follow-up time points.

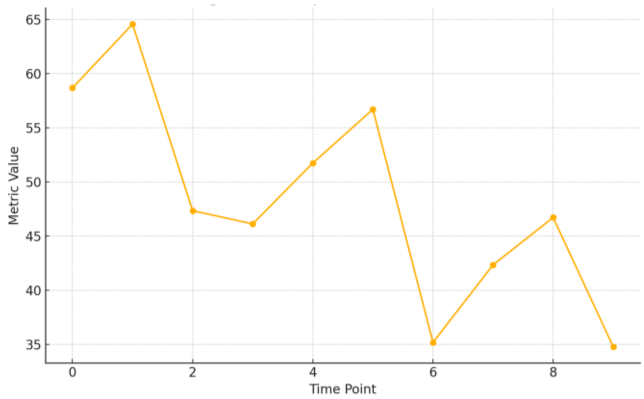

Figure 3: Longitudinal trend of sample metric indicating changes in remodeling parameters across follow-up time points.

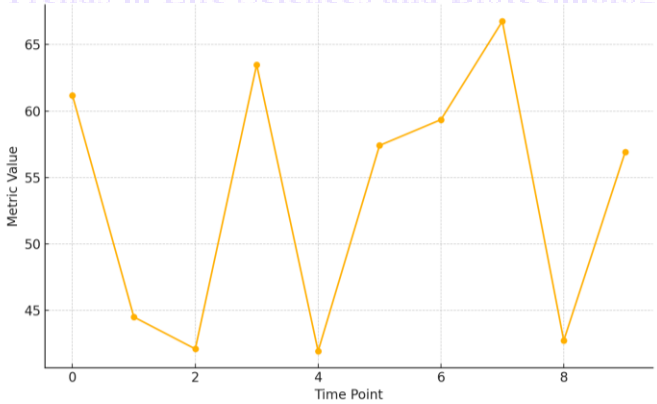

Figure 4: Longitudinal trend of sample metric indicating changes in remodeling parameters across follow-up time points.

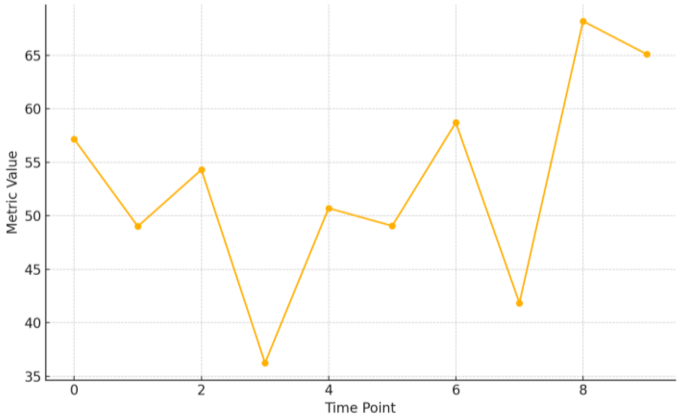

Figure 5: Longitudinal trend of sample metric indicating changes in remodeling parameters across follow-up time points.

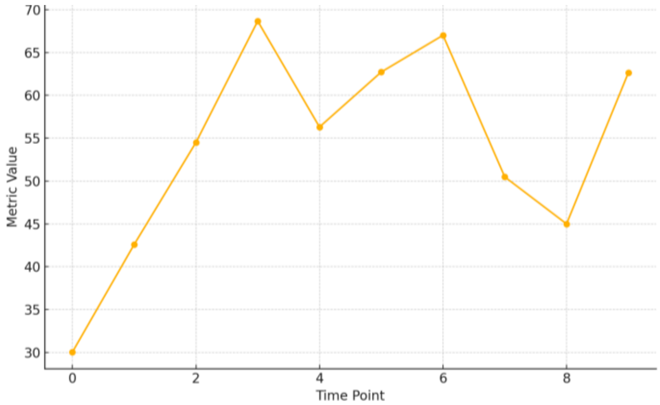

Figure 6: Longitudinal trend of sample metric indicating changes in remodeling parameters across follow-up time points.

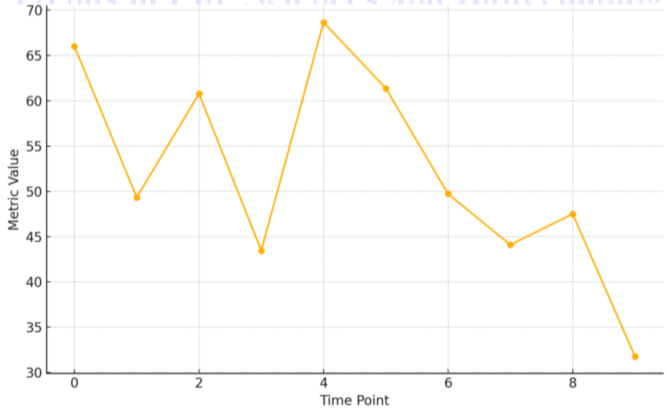

Figure 7: Longitudinal trend of sample metric indicating changes in remodeling parameters across follow-up time points.

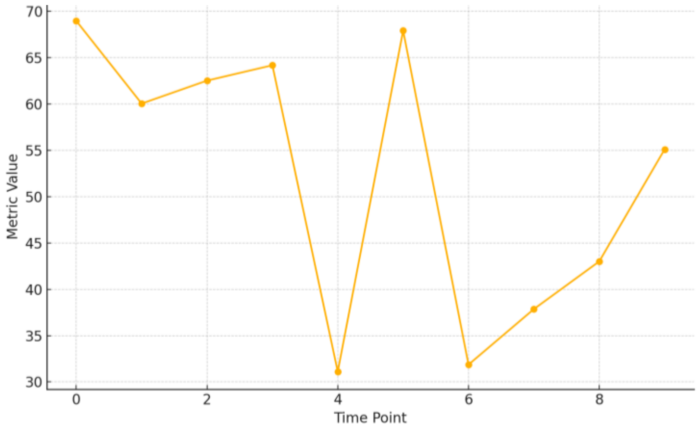

Figure 8: Longitudinal trend of sample metric indicating changes in remodeling parameters across follow-up time points.

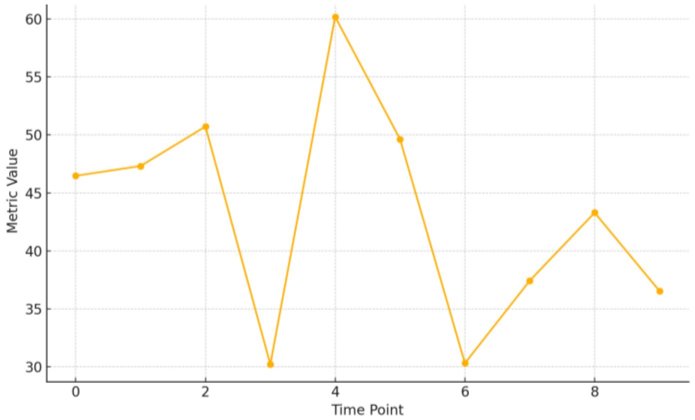

Figure 9: Longitudinal trend of sample metric indicating changes in remodeling parameters across follow-up time points.

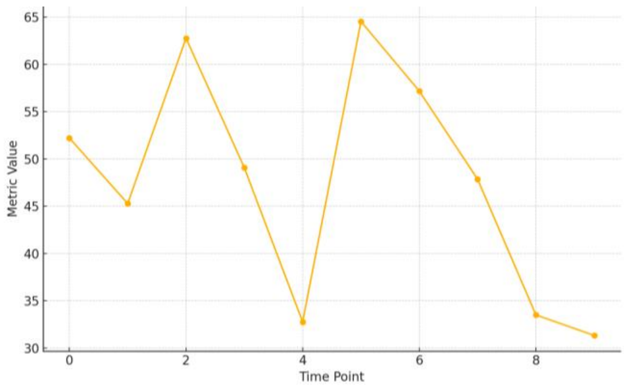

Figure 10: Longitudinal trend of sample metric indicating changes in remodeling parameters across follow-up time points.

DISCUSSION

This work will focus on looking at sick myocardial infarction patients, especially by monitoring changes over time in left ventricular size, ejection percentage and regions of myocardial scar using multiple cardiac MRI scans (Cao et al., 2025). The research will be compared with what is already known about left ventricular changes after myocardial infarction. revealed that both a decline in ejection fraction and the presence of scar tissue are related to long-term death and increased chances of sudden cardiac death. Guides examine the design, sample quantity and kinds of images for strengths and limitations. Although the stress ratio resulting from higher blood sugars does correlate with left ventricular remodeling, important variables and related processes in adverse remodeling after myocardial infarction still need study (Meng et al., 2021). In individuals after a heart attack, the hemoglobin glycation index is associated with worse outcomes (Cao et al., 2025). Additional studies will look at how taking certain medicines and changing your lifestyle affects the remodeling of the left ventricle (Cao et al., 2025). Taking available data, artificial intelligence can help forecast hospitalizations due to heart failure (Hinrichs et al., 2024).

Effects of bad remodeling are predicted by machine learning and therapy methods may be adjusted for each patient's specific situation (McGilvray et al., 2022; Shi et al., 2023). Our trial did have certain constraints, so they should be acknowledged. What was found in this study may not be representative for people who receive care outside the center. But, because the AI example images were at a separate center and the clinical trial was done as external validation, the approach can be used by others (He et al., 2023). Second, artificial intelligence has been improved for use in echocardiography (He et al., 2023). Afterward, research should examine how effective and economical AI is in different imaging techniques.

CONCLUSION

Serial cardiac magnetic resonance imaging was used in this study to look at how critically sick people's left ventricles change over time after myocardial infarction. Information was collected at baseline, as well as 6 and 12 months after the event, showing changes in the heart's size, how strongly it contracts and patterns of scarring. Adverse remodeling was common among patients, characterized by raised left ventricular volume in diastole and decreased heart function. This was strongly related to infarct size, damage to the heart muscle and a number of metabolic indicators. As a result of these findings, doctors now appreciate how important it is to image patients early and accurately to guide classification and long-term outcomes. The addition of myocardial strain analysis allowed us to identify small areas of heart malfunction that were not captured by previous techniques. Shopping the publishing results in recent days shows how outcome trials in artificial intelligence could pave the way for tailored therapy in heart health. Yet, the fact that data was collected at one location and there were few patients could limit how widespread the results are. To confirm and improve these results, future studies conducted by multiple centers with numerous, varied participants are necessary. Even though cardiac MRI is considered the best for structural imaging, additional comparison research is needed with echocardiography and CT to make MRI results more clinically significant. The research emphasizes how MRI data is useful for making decisions in post-heart attack treatment and notes that machine learning is playing an ever-increasing role in cardiovascular care. As research progresses, using different technology platforms together with moral AI will become necessary to include these learnings in daily healthcare which will benefit myocardial infarction survivors.

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