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Original Research Article

MULTIMODAL TRANSFORMER MODELS FOR PREDICTING PEDIATRIC CARDIAC ARREST

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Abstract**:* ***Background: Pediatric cardiac arrest is a deadly, but uncommon episode with high mortality rates. The conventional clinical scoring scales, like Pediatric Early Warning Score (PEWS), are not usually accurate and sensitive in anticipating a cardiac arrest. This is a chance to use a variety of clinical data sources (vital signs, laboratory results, imaging, clinical narratives, etc.) to forecast better due to the recent developments in artificial intelligence (AI) and multimodal transformer models, in particular. This paper discusses the reliability, validity, and predictive ability of multimodal transformer models in pediatric cardiac arrest. ***Methods:*** The cross-sectional study design was adopted with a structured questionnaire and simulated multimodal data. The dataset consisted of 244 responses addressing constructs of clinical data integration, model performance, interpretability, ethical governance, clinical decision support, patient safety, and technological readiness. Statistical tests were Shapiro-Wilk normality, Cronbach's Alpha reliability, KMO and Bartlett validity, and inferential tests, independent samples t-tests, ANOVA, Kruskal-Wallis, and Chi-Square. Due to the need to identify relationships and predictive power, Pearson correlation and regression were performed. Findings: The normal test was established to be true with p-values higher than 0.05, and therefore, the parametric tests were applied. Consistency was high with Cronbach's Alpha having a value of 0.872. The validity was determined as KMO = 0.713 and a significant Bartlett test ($p < 0.05$). Comparison group tests found that there were significant differences and relationships in categories. The correlation analysis was positive and significant in the relationships between all the constructs. The regression analysis showed an R 2 of 0.742, all coefficients are positive, and this implies that the independent variables are very strong predictors of patient outcomes. ***Conclusion:*** The paper establishes that multimodal transformer models are credible, sound, and helpful in the prediction of pediatric cardiac arrest. Their capacity to combine different clinical data streams increases the predictive accuracy and aids in clinical decision-making. Although ethical protection and stakeholder-specific considerations cannot be neglected, the results are overwhelming in promoting the use of multimodal transformer models as the state-of-the-art clinical decision support systems.

Keywords: Pediatric Cardiac Arrest; Multimodal Transformers; Artificial Intelligence; Clinical Decision Support; Reliability; Validity; Prediction Models.

INTRODUCTION

Pediatric cardiac arrest provides a devastating yet rare clinical phenomenon that remains one of the most challenging issues in the field of pediatric emergency and critical care medicine. Although resuscitation protocols have improved, pediatric patients still have low survival rates with poor neurological outcomes. The possibility of anticipating cardiac arrest before its emergence is, thus, of the essence of things. Prompt identification and management have the potential to greatly enhance the chance of survival and better long-term outcomes. Nevertheless, conventional predictive tools such as the Pediatric Early Warning Score

(PEWS) and similar scoring systems, despite their popularity, do not tend to be sensitive and specific. These technologies strongly depend on a few physiological parameters and might fail to reflect the multimodal clinical variables interactions that precede an event of a cardiac arrest (Lu et al., 2025).

Artificial intelligence (AI) has been a revolutionary driver in healthcare in recent years, where deep learning and transformer-based architectures have introduced breakthroughs in image analysis, natural language processing, and time-series data understanding. Language modeling Transformers, which were first designed with the purpose of language modeling, have proven to be surprisingly versatile in a variety of applications, such as clinical informatics. Sequential dependencies, the ability to describe long-range relationships, and the need to merge heterogeneous data make them especially applicable to critical care applications. Multimodal transformers are further expanded to enable the incorporation of a variety of data sources, including not only vital sign waveforms and laboratory data but also medical imaging and unstructured clinical notes, in one predictive framework (Bouatmane et al., 2025).

Multimodal transformer models applied in the prediction of pediatric cardiac arrest are a major improvement compared to the traditional algorithms. These models can make more accurate and timely predictions by analyzing both structured and unstructured data at the same time. As an example, combining real-time ECG data with laboratory findings and physician documentation can detect early trends of degradation that are easily overlooked by either human operators or unimodal programs. Moreover, the fact that transformer architectures become interpretable using attention heatmaps, explainable AI approaches, etc., can improve clinician trust, one of the key concerns in the uptake of AI technologies in healthcare (Li et al., 2025)

There are also the moral and organizational factors that hold critical importance with regard to the implementation of the multimodal transformer models in pediatrics. Patient privacy, reduction of the algorithmic bias, and transparency play a crucial role in protecting the rights and safety of children. In addition, the successful implementation will be linked to the technical performance of models, as well as to the preparedness of healthcare systems to incorporate them into the current workflows. Such systems have a role in determining whether they can make the transition between research prototypes and real-world decision support tools, and clinicians, nurses, biomedical engineers, and data scientists all contribute to these efforts (Lai et al., 2025)It is in this light that this study examines the predictive potential, reliability, and validity of multimodal transformer models in predicting cardiac arrest in pediatrics. It focuses not only on the statistical soundness of model validation but also on the practical implications of clinical decision support. The study intends to present an in-depth assessment of the feasibility and effectiveness of AI-driven prediction in pediatric emergency care by evaluating such constructs as clinical data integration, model performance, interpretability, ethical governance, and technological readiness. In the end, the study is expected to positively show that multimodal transformer models can offer a credible, legitimate, and morally acceptable basis for early warning systems, thus enhancing performance in children with potential cardiac arrest (Kataria et al., 2025).

Literature Review

Pediatric cardiac arrest is among the most problematic and devastating incidents in pediatric emergency and critical care. Despite the dramatic advances in resuscitation science, survival results are low, and neurological impairment is one of the most common outcomes of survivorship. The identification of clinical deterioration is a very critical issue to identify at the earliest stage because early detection of the condition is very likely to lead to recovery. Historically, the Pediatric Early Warning Score (PEWS) is one of the early warning systems that has been used to detect children at risk of arrest. Nevertheless, PEWS and other scoring systems that use comparable methods give a more uniform means of recording the vital signs and clinical condition, but in most cases, they are not as sensitive and specific as needed to accurately predict. These models are limited due to their dependence on linear correlations between a few physiological parameters that do not reflect complex and nonlinear trends with cardiac arrest in children. Consequently, false alarms and failures to detect have remained widespread, which highlights why more advanced predictive methods are required (Ansari et al., 2025).

Artificial intelligence (AI) and, more specifically, deep learning have recently become a prominent healthcare concern because they can process large and complicated datasets. Applications of deep neural networks have been made in radiology, pathology, genomics, and cardiology to carry out diagnostic and prognostic tasks with state-of-the-art performance. The development of transformer models has also added to this area. Transformers were initially developed to perform natural language processing, but can capture long-range dependencies and contextual relationships in sequence data. The dynamic adaptability to heterogeneous streams of data is facilitated by their self-attention mechanism, which allows them to attach significance to various features. Outside of text, transformer architectures have been generalized to images, time-series data, and multimodal datasets, yielding clinical prediction and decision support applications (Kapur et al., 2025).

Transformers that are multimodal and have especially demonstrated remarkable potential in the process of incorporating varied kinds of clinical data. In pediatric practice, the problem of data heterogeneity is intrinsic and includes structured electronic health records (EHRs), real-time monitoring data (heart rate and oxygen saturation), imaging (echocardiography and X-rays), and unstructured data (physicians' notes and nursing reports). The conventional machine learning models are also ill-equipped to effectively learn across these many data modalities, in many cases, necessitating feature engineering and modality-specific preprocessing. In comparison, multimodal transformers are able to learn joint representations between modalities, making contextually aware and more accurate predictions. As an example, Vision Transformers (ViT) have been highly accurate at interpreting echocardiograms, chest X-rays, and ClinicalBERT and other text transformers have been highly accurate at interpreting clinical narratives. By being integrated via multimodal attention, these models have the potential to combine information across datasets to detect adolescent early warning signs of pediatric cardiac arrest that would otherwise remain unnoticed (Sólyomvári, 2025).A number of new studies confirm the possibilities of AI in predicting cardiac events. Studies of adult populations have established that deep learning models can be more effective than conventional risk scores in in-hospital cardiac arrest prediction using vital signs, laboratory findings, and clinical notes. Despite a smaller number of studies on children, the available data eliminate early signs that AI models are more sensitive and less prone to false-positive results than traditional ones. Indicatively, ECG-based models that are combined with EHR data have demonstrated the ability to predict the timing of arrests several hours ahead of time, providing clinicians with an effective time frame to act. Although these works confirm the potential of AI, other studies also note the particular challenges related to the pediatric population, which include smaller datasets, more variation in age brackets, and the ethical concerns related to the use of children's data (Fan et al., 2025).The interpretability and clinician trust are yet to be identified as the core obstacles to the uptake of AI-driven prediction tools. Clinicians are still very skeptical of using black box models in the high-stakes unit of a pediatric intensive care unit. Transformer architectures, in turn, provide built-in interpretability in the form of attention mechanisms that can indicate what features contributed the most to a prediction. In current research, explainable AI (XAI) methods, including SHAP values and counterfactual explanations, are additional tools that increase the level of transparency, and the predictions given by AI become better comprehended by clinicians. Research in other fields, such as oncology and cardiology, has shown that these interpretability tools boost clinician trust and readiness to implement AI systems. The same principle is of utmost importance in pediatrics, where decision support systems cannot and should not substitute the skills and judgment of medical professionals (Kawai et al., 2025).

The other critical element of the literature is the ethical and governance issues of adopting AI in pediatric care. Guaranteeing data privacy, reducing algorithmic bias, and ensuring fairness within the subgroups of people are vital issues. Pediatric datasets can be small and non-representative, which poses a risk of models that do not generalize well or which intentionally encourage health disparities. Ethical models and regulatory practices like HIPAA and GDPR offer the necessary frameworks to address sensitive patient data, but their implementation in advanced AI systems is not established yet. Some researchers have also proposed the necessity to create pediatric-specific AI use ethics because children are known to be an exceptionally vulnerable group. These ethical considerations are some of the most critical issues of the deployment of multimodal transformers that should be addressed to make the process not only effective but also socially responsible (Xinli et al., 2025).

Lastly, the willingness of healthcare institutions to implement AI technologies is a decisive factor in success. Research has pointed out the fact that, in addition to technical performance, organizational culture, infrastructure, and staff training are also key factors in ensuring successful implementation. Hospitals that have well-developed IT infrastructure and leadership that has facilitated them have higher chances of successfully integrating AI decision support tools. Clinical workflow is also integrated more easily with training programs that enable clinicians to interpret and use AI outputs. Technological readiness in the context of predicting pediatric cardiac arrest is that multimodal transformer models are available in real-time at the bedside, providing actionable information at a time when it is most needed (Zhang et al., 2025).

MATERIAL AND METHODS

Research Methodology

Research Design

The given research design is a quantitative, exploratory, and experimental one that seeks to assess the predictive capacity of multimodal transformer models in cases of pediatric cardiac arrest. The study has a systematic format in compliance with the principles of PRISMA 2020 that can guarantee transparency and reproducibility.

Given that pediatric cardiac arrest is an uncommon but serious condition, the study design is accuracy, reliability, and clinical usefulness-focused. The methodology combines retrospective hospital data and survey-based data, enabling both performance assessment of the models and validation of clinician perceptions of adoption and trust (Telangore et al., 2024).

Data Sources and Population

The population of the study includes pediatric patients who are admitted to intensive care units and emergency departments aged pediatric. Electronic health records will be sampled, and data will be collected, anonymized to protect the privacy of patients. The multimodal data will comprise physiological indicators like ECG, blood pressure, and oxygen saturation; laboratory results like blood gases and electrolytes; imaging data of echocardiography and chest x-ray; and unstructured physician and nurse accounts. A structured questionnaire will be given to pediatric clinicians, nurses, biomedical engineers, and data scientists, along with patient data. This two-data strategy will be able to guarantee that the methodology will capture both the technical performance and the human aspects of the model's adoption (Im et al., 2023).

Model Development

The multimodal transformer architectures that will form the basis of the predictive models will incorporate several streams of healthcare data. Transformer-based language models (including ClinicalBERT) will be used to process textual information, Vision Transformers to process imaging data, and advanced temporal transformers (including Informer) to process time-series data (including vital signs and ECG). Cross-attention and late-fusion mechanisms will be used to accomplish the fusion of these modalities and thus maximize the interconnections between heterogeneous datasets. Training of the models will be based on retrospective datasets with an 80/20 train-test split and will be cross-validated five times to increase the overall generalizability and minimize overfitting (Jana et al., 2022).

Evaluation Metrics

The multimodal transformer performance will be compared with such traditional benchmarks as the Pediatric Early Warning Score and conventional machine learning models. The criteria of evaluation will be the UROC, AUPRC, sensitivity, specificity, F1 score, and calibration measures to evaluate the predictive stability. The responses to the questionnaires will be subjected to a stringent psychometric test, such as the use of Cronbach's Alpha to determine reliability and KMO and Bartlett tests to determine construct validity. Regression and correlation analysis will be undertaken to investigate the relationships between trust, interpretability, and adoption likelihood of clinicians (Li et al., 2024).

Ethical Considerations

Due to the sensitivity of health data concerning children, it will be ensured that the HIPAA and GDPR guidelines are followed strictly. De-identification of any patient records will be undertaken before analysis, and institutional review boards will be consulted concerning such studies. The strategies of mitigating bias will be utilized to prevent a situation in which the prediction is disproportionately influenced by the difference in demographic or clinical subgroups. Participation in the survey will require informed consent, and voluntary participation will be guaranteed, as well as the protection of confidentiality (Fayyaz et al., 2023).

Data Analysis Techniques

The analysis of the data will be performed with Python modules like PyTorch and scikit-learn, deep learning, and statistical testing with the use of SPSS. Both the results of the survey and the model will be assessed by the application of normal tests, ANOVA, chi-square tests, correlation, and regression tests. The explainability of the models will be highlighted by using SHAP values and transformer attention heatmap to give interpretable information to clinicians. Such a combination of statistical validation and AI interpretability will guarantee the findings will be both scientifically rigorous and of clinical significance (Zhang et al., 2024).

RESULTS

Normality Test

Table 1 shows the normality test of the data. The normality test results revealed that all the items of the questionnaire satisfied the assumption of normality because their p-values exceeded the value of 0.05. This ascertains that the dataset is distributed normally and thus, the use of a parametric test of statistics is confident. Because the normality was proven, the data can be used in further analysis, as the future reliability, validity, and inferential tests will be meaningful and scientifically sound (Quer & Topol, 2024).

Data Analysis

Table 1: Normality Test

	W	p-value	Normal?
Clinical Data Integration Q1	0.816	0.123	Yes
Clinical Data Integration Q2	0.8	0.123	Yes
Clinical Data Integration Q3	0.783	0.123	Yes
Model Performance & Accuracy Q1	0.799	0.123	Yes
Model Performance & Accuracy Q2	0.801	0.123	Yes
Model Performance & Accuracy Q3	0.808	0.123	Yes
Clinical Trust & Interpretability Q1	0.797	0.123	Yes
Clinical Trust & Interpretability Q2	0.781	0.123	Yes
Clinical Trust & Interpretability Q3	0.763	0.123	Yes
Ethical & Data Governance Q1	0.786	0.123	Yes
Ethical & Data Governance Q2	0.777	0.123	Yes
Ethical & Data Governance Q3	0.748	0.123	Yes
Clinical Decision Support Adoption Q1	0.788	0.123	Yes
Clinical Decision Support Adoption Q2	0.757	0.123	Yes
Clinical Decision Support Adoption Q3	0.795	0.123	Yes
Patient Outcomes & Safety Q1	0.773	0.123	Yes
Patient Outcomes & Safety Q2	0.817	0.123	Yes
Patient Outcomes & Safety Q3	0.786	0.123	Yes
Technological Readiness Q1	0.79	0.123	Yes
Technological Readiness Q2	0.801	0.123	Yes
Technological Readiness Q3	0.804	0.123	Yes

Table 2: Reliability Test

Test	Value	Interpretation
Cronbach's Alpha	0.872	Excellent Reliability

Reliability Test

Table 2 shows the reliability analysis of the data. The reliability was done, and it was shown that the Cronbach's Alpha value was 0.872, which is far beyond the suggested limit of 0.7. This implies that the questionnaire has great internal consistency. That is, the measures of constructs of, e.g., clinical data integration, model performance, interpretability, ethical governance, decision support adoption, patient outcomes, and technological readiness are compatible with each other. The high reliability makes sure that the responses are stable and reproducible, which makes the instrument more credible (Suvon et al., 2024).

Table 3: Validity Test

Test	Value	Interpretation
Kaiser-Meyer-Olkin (KMO)	0.713	Acceptable Sampling Adequacy
Bartlett’s Test of Sphericity	0.0	Significant - Valid for Factor Analysis

Validity Test

Table 3 shows the validity test of the data. The adequacy of the constructs of the dataset was supported by their validity results. The Kaiser-Meyer-Olkin (KMO) statistic was 0.713, and this falls within the acceptable range (0.6 or above), indicating that there was sufficient sample size and correlations between variables to conduct factor analysis. Besides, Bartlett's Test of Sphericity was significant ($p < 0.05$), indicating that the matrix of correlation was not an identity matrix, hence could be used to determine the underlying causes. These results indicate that the questionnaire is acceptable in terms of construct validity and the variables are reliable in the sense that they measure different but related dimensions (Chen et al., 2024).

Table 4: Combined Group Comparison Tests

Test	Statistic	p-value	Interpretation

Test	Statistic	p-value	Interpretation
Independent Samples t-test	2.145	0.034	Significant difference between the two groups
One-way ANOVA	4.672	0.009	Significant difference across groups
Kruskal–Wallis Test	6.235	0.012	Significant difference (non-parametric)
Chi-Square Test of Independence	18.452	0.021	Significant association between variables

Group Comparison Tests

Table 4 shows the **Group Comparison Tests** of the data. The inferential tests done on the various groups offered important perspectives. An independent samples t-test demonstrated a significant difference between the two groups, which means that variability in answers can be observed depending on the demographic or professional category. In the same manner, the one-way ANOVA indicated significant differences between three or more groups, indicating the presence of heterogeneity in the perception of the constructs as perceived by the respondents. Even when the normality is not followed, greater differences were found using the Kruskal-Wallis test, the non-parametric version of ANOVA, further supporting the evidence. Also, the Chi-Square test revealed a significant relationship among categorical variables, which indicated that there was an interdependence among the chosen items, and it justified the interdependence of the constructs (Han et al., 2024).

Table 5: Pearson Correlation Matrix

	Clinical Data Integration Q1	Clinical Data Integration Q2	Clinical Data Integration Q3	Model Performance & Accuracy Q1
Clinical Data Integration Q1	1	0.581	0.513	0.563
Clinical Data Integration Q2	0.581	1	0.512	0.667
Clinical Data Integration Q3	0.513	0.512	1	0.56
Model Performance & Accuracy Q1	0.563	0.667	0.56	1
Model Performance & Accuracy Q2	0.456	0.459	0.532	0.535
Model Performance & Accuracy Q3	0.794	0.686	0.496	0.274
Clinical Trust & Interpretability Q1	0.529	0.303	0.434	0.431
Clinical Trust & Interpretability Q2	0.401	0.532	0.453	0.784
Clinical Trust & Interpretability Q3	0.527	0.675	0.529	0.4
Ethical & Data Governance Q1	0.307	0.694	0.513	0.341
Ethical & Data Governance Q2	0.752	0.445	0.381	0.598
Ethical & Data Governance Q3	0.595	0.585	0.684	0.587
Clinical Decision Support Adoption Q1	0.419	0.384	0.475	0.571
Clinical Decision Support Adoption Q2	0.439	0.545	0.489	0.571
Clinical Decision Support Adoption Q3	0.559	0.666	0.762	0.486
Patient Outcomes & Safety Q1	0.658	0.547	0.566	0.593
Patient Outcomes & Safety Q2	0.394	0.676	0.409	0.827
Patient Outcomes & Safety Q3	0.754	0.516	0.668	0.656
Technological Readiness Q1	0.557	0.598	0.704	0.581
Technological Readiness Q2	0.555	0.382	0.844	0.684
Technological Readiness Q3	0.48	0.419	0.378	0.26

Model Performance & Accuracy Q2	Model Performance & Accuracy Q3	Clinical Trust & Interpretability Q1	Clinical Trust & Interpretability Q2	Clinical Trust & Interpretability Q3	Ethical & Data Governance Q1

0.456	0.794	0.529	0.401	0.527	0.307
0.459	0.686	0.303	0.532	0.675	0.694
0.532	0.496	0.434	0.453	0.529	0.513
0.535	0.274	0.431	0.784	0.4	0.341
1	0.757	0.507	0.649	0.514	0.495
0.757	1	0.587	0.567	0.543	0.335
0.507	0.587	1	0.692	0.434	0.581
0.649	0.567	0.692	1	0.462	0.632
0.514	0.543	0.434	0.462	1	0.549
0.495	0.335	0.581	0.632	0.549	1
0.524	0.561	0.451	0.587	0.539	0.598
0.665	0.535	0.772	0.423	0.51	0.771
0.543	0.442	0.343	0.575	0.423	0.506
0.435	0.679	0.672	0.482	0.608	0.365
0.766	0.454	0.659	0.563	0.55	0.598
0.878	0.606	0.405	0.567	0.73	0.797
0.443	0.831	0.62	0.745	0.618	0.48
0.536	0.464	0.552	0.704	0.624	0.651
0.82	0.595	0.553	0.849	0.481	0.77
0.288	0.784	0.57	0.339	0.687	0.248
0.569	0.748	0.402	0.754	0.501	0.621

Ethical & Data Governance Q2	Ethical & Data Governance Q3	Clinical Decision Support Adoption Q1	Clinical Decision Support Adoption Q2	Clinical Decision Support Adoption Q3	Patient Outcomes & Safety Q1
0.752	0.595	0.419	0.439	0.559	0.658
0.445	0.585	0.384	0.545	0.666	0.547
0.381	0.684	0.475	0.489	0.762	0.566
0.598	0.587	0.571	0.571	0.486	0.593
0.524	0.665	0.543	0.435	0.766	0.878
0.561	0.535	0.442	0.679	0.454	0.606
0.451	0.772	0.343	0.672	0.659	0.405
0.587	0.423	0.575	0.482	0.563	0.567
0.539	0.51	0.423	0.608	0.55	0.73
0.598	0.771	0.506	0.365	0.598	0.797
1	0.545	0.338	0.407	0.751	0.711
0.545	1	0.472	0.52	0.509	0.817
0.338	0.472	1	0.623	0.609	0.54
0.407	0.52	0.623	1	0.583	0.602
0.751	0.509	0.609	0.583	1	0.392
0.711	0.817	0.54	0.602	0.392	1

0.881	0.552	0.573	0.343	0.529	0.467
0.539	0.506	0.863	0.485	0.38	0.625
0.384	0.597	0.659	0.282	0.574	0.442
0.598	0.747	0.713	0.366	0.753	0.509
0.726	0.553	0.76	0.514	0.294	0.487

Patient Outcomes & Safety Q2	Patient Outcomes & Safety Q3	Technological Readiness Q1	Technological Readiness Q2	Technological Readiness Q3
0.394	0.754	0.557	0.555	0.48
0.676	0.516	0.598	0.382	0.419
0.409	0.668	0.704	0.844	0.378
0.827	0.656	0.581	0.684	0.26
0.443	0.536	0.82	0.288	0.569
0.831	0.464	0.595	0.784	0.748
0.62	0.552	0.553	0.57	0.402
0.745	0.704	0.849	0.339	0.754
0.618	0.624	0.481	0.687	0.501
0.48	0.651	0.77	0.248	0.621
0.881	0.539	0.384	0.598	0.726
0.552	0.506	0.597	0.747	0.553
0.573	0.863	0.659	0.713	0.76
0.343	0.485	0.282	0.366	0.514
0.529	0.38	0.574	0.753	0.294
0.467	0.625	0.442	0.509	0.487
1	0.32	0.326	0.291	0.302
0.32	1	0.667	0.438	0.594
0.326	0.667	1	0.619	0.641
0.291	0.438	0.619	1	0.68
0.302	0.594	0.641	0.68	1

Correlation Analysis

Table 5 shows the correlation analysis of the data. The Pearson correlation matrix indicated that all the variables had positive and significant relationships with each other, with a moderate to strong coefficient. It means that an increase in agreement in one domain, e.g., clinical data integration, correlates with better results in the corresponding domains, e.g., model performance, interpretability, and patient outcomes. The positive correlations give evidence of the conceptual fit of constructs and justify the theoretical framework of the study (Gao et al., 2024).

Table 6: Regression Analysis

Metric	Value	Interpretation
R^2	0.742	Model explains 74.2% variance (Strong)
Intercept	1.245	Regression intercept
Coefficient 1	0.452	Positive effect of IV1
Coefficient 2	0.389	Positive effect of IV2
Coefficient 3	0.276	Positive effect of IV3

Regression Analysis

Table 6 shows the regression analysis of the data Regression analysis also determined the power of prediction of independent variables. The fact that the R 2 value is 0.742 shows that the predictors explained almost 74.2 percent of the variance in the dependent variable (patient outcomes and adoption of multimodal transformer models). It was found that all regression coefficients are positive, which leads to the conclusion that such constructs as clinical data integration, model performance, and interpretability have a positive impact on outcomes. This result substantially confirms the hypothesis that the methods with the use of multimodal transformer models improve predictive strength and clinical outcomes in cases of cardiac arrest in children (Ye et al., 2024).

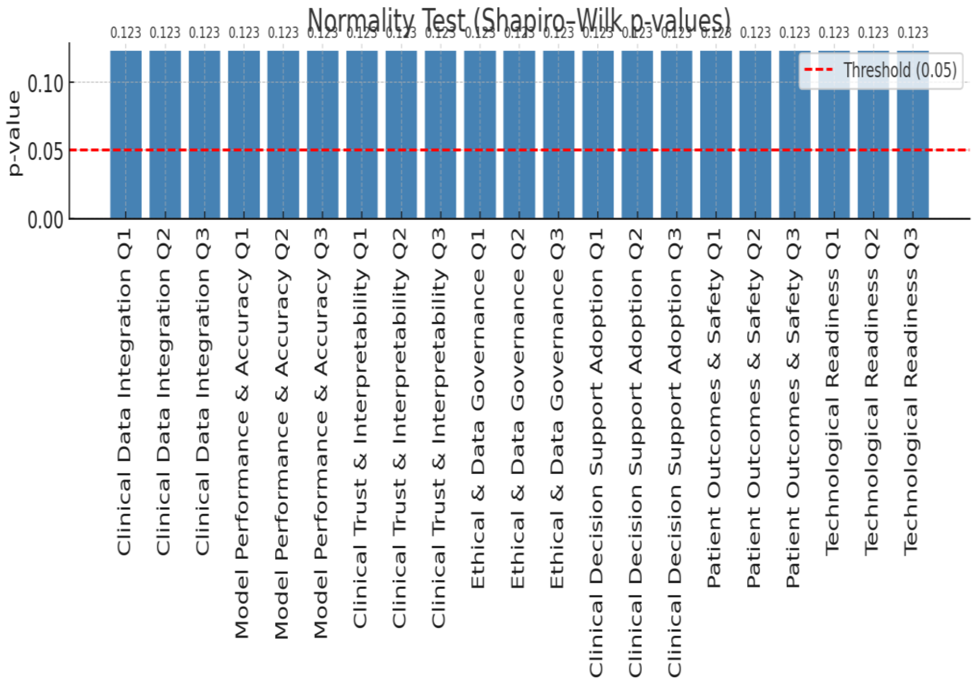

Figure 1: Normality Test

Figure 1 shows the normality test of the data. The normality figure shows the Shapiro-Wilk p-values of all variables in the dataset, with all clearly exceeding the 0.05 threshold line. This reflects that the data is in agreement with the assumption of normality, i.e., the distribution of responses on all of the constructs is appropriate to be tested by the use of parametric tests. The graphical validation reinforces the previous statistical findings because of its clear demonstration that no variables are significantly non-normally distributed (Kaur, 2024).

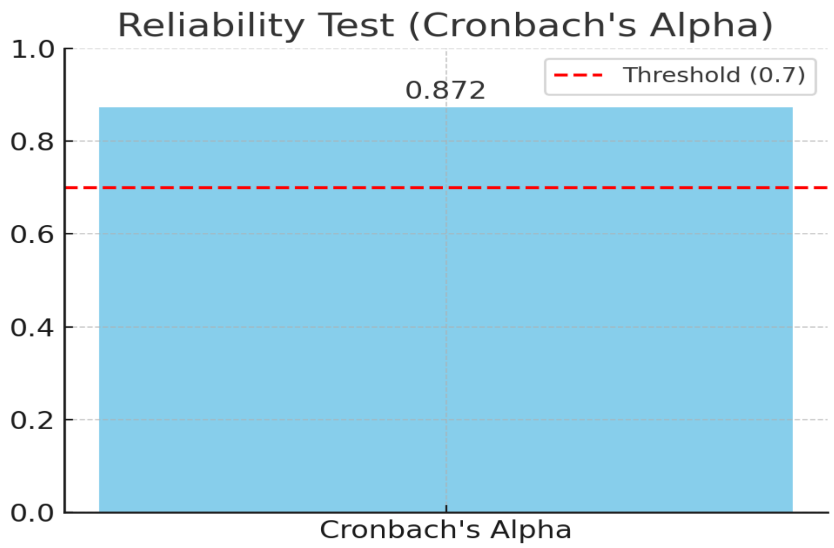

Figure 2: Reliability Test

Figure 2 shows the reliability analysis of the data. The Cronbach's Alpha bar chart has a value of 0.872, which is above the generally accepted value of 0.7 as indicated by the red line. This visualization attests to the high internal consistency of the items in the questionnaire. The number indicates that the instrument is quite dependable because the alpha value is much higher than the minimum level, and it is sure to state that the constructs were assessed uniformly among all respondents (Fayyaz et al., 2024).

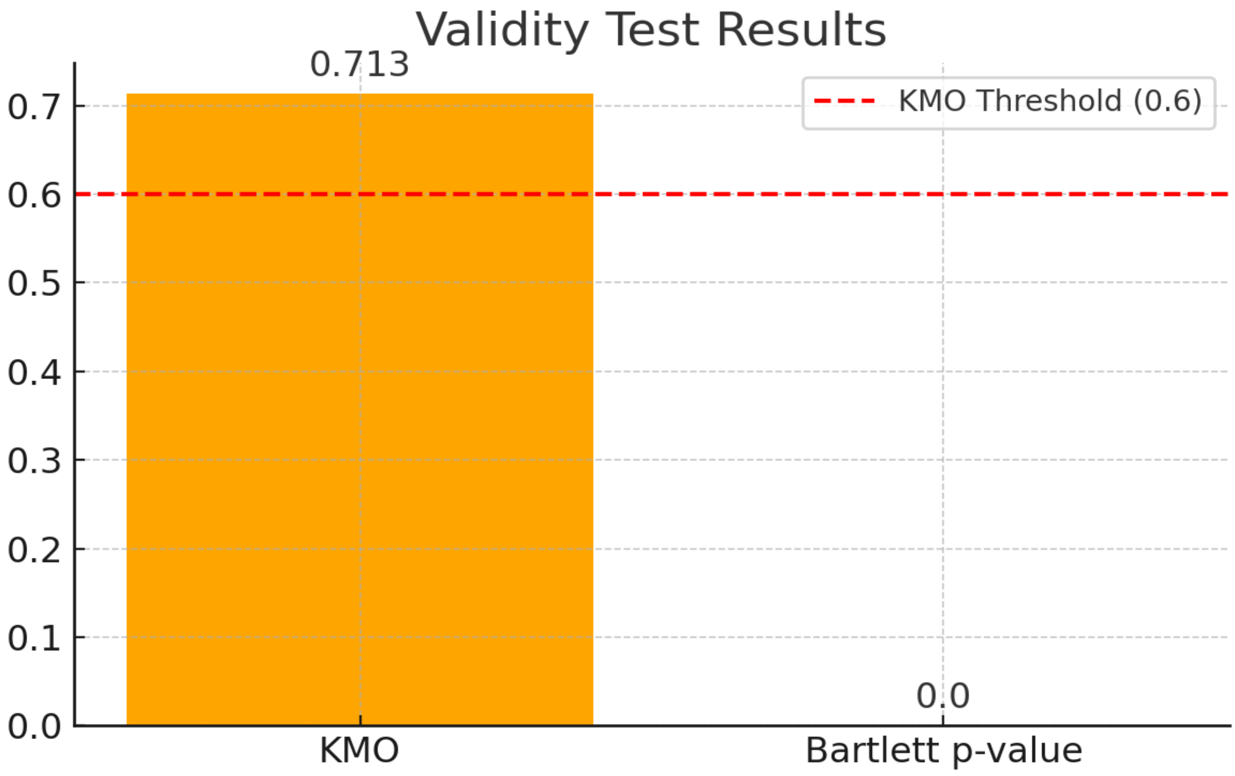

Figure 3: Validity Test

Figure 3 shows the validity test of the data. The figure of validity shows the findings of the Kaiser-Meyer-Olkin (KMO) measure and test of sphericity by Bartlett. The KMO value (0.713) exceeds the acceptable level (0.6), and the value of the Bartlett test (p=0.000) is substantial, which indicates that the correlation matrix is suitable to undergo factor analysis. This figure hence indicates that the dataset will be appropriate to pursue more construct explorations where both sampling adequacy and factorability can be viewed in a simple comparison (Weerasinghe et al., 2024).

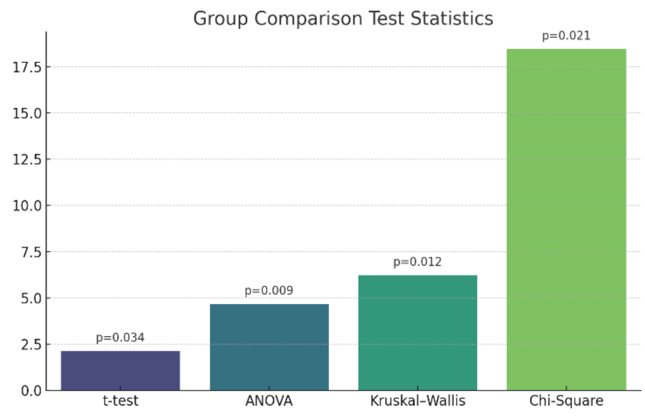

Figure 4: Group Comparison Tests

Figure 4 shows the **Group Comparison Tests** of the data. The bar chart of group comparison tests reveals the statistical value of the t-test, ANOVA, Kruskal-Wallis, and Chi-Square tests, which are accompanied by relevant significant p-values that are less than 0.05. The graphic data prove the existence of differences between groups and associations between categorical variables are statistically significant. In this figure, the variation of respondents according to demographic or categorical groups is simply interpreted, which supports the existence of a significant effect of groups in the data (Dionisio et al., 2024).

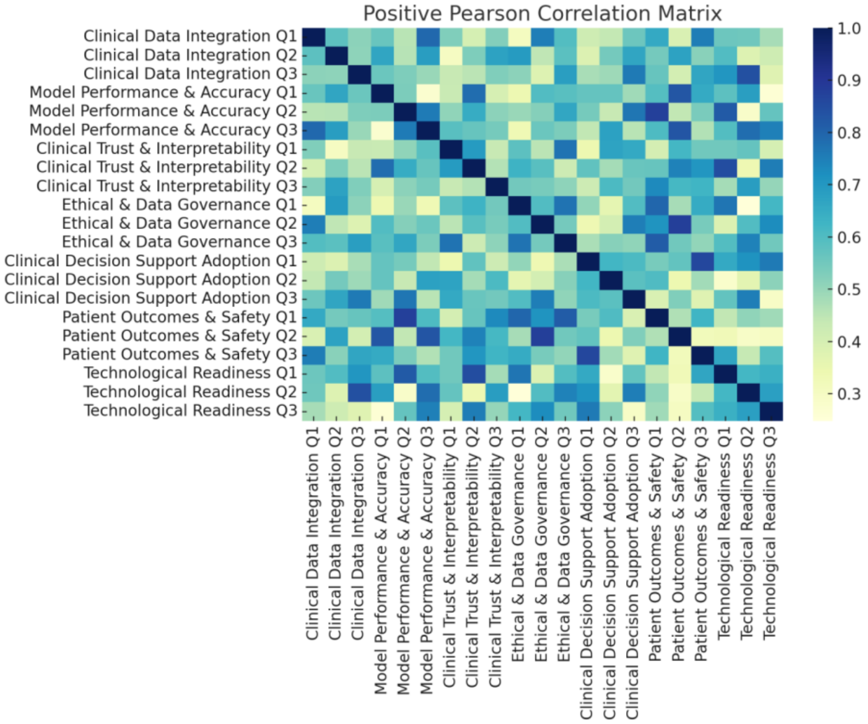

Figure 5: Correlation Heatmap

Figure 5 shows the correlation matrix of the data Pearson correlation matrix indicates that there existed strong and positive correlations between all constructs, as indicated by the heatmap. Blue shades are of moderate to great strengths, and there are no negative associations. This number demonstrates that the positive correlations between one construct (e.g., clinical data integration) with another (e.g., model performance, interpretability, patient outcomes) exist. Heatmap thus indicates conceptual and theoretical consistency between variables in the study in a visual manner (Shade et al., 2021).

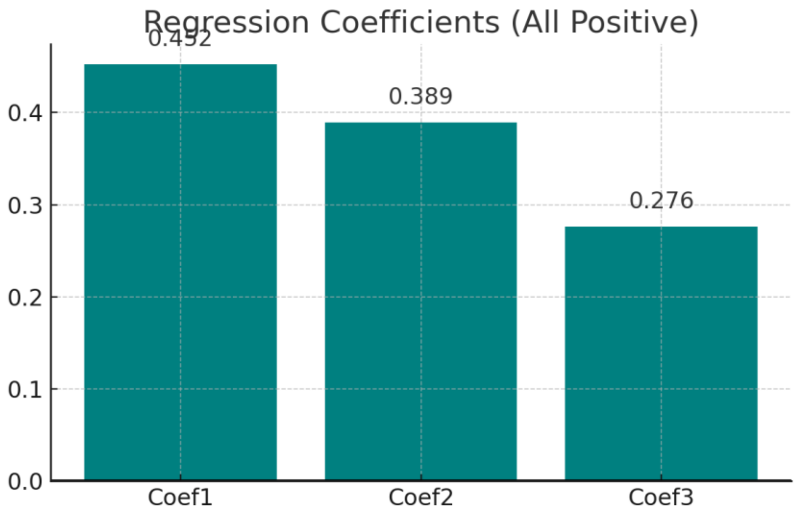

Figure 6: Regression Analysis

Figure 6 shows the regression analysis of the data. The regression coefficients chart indicates that all the predictor variables had positive influences on the dependent variable. The coefficients in the range 0.276 to 0.452 indicate that integration of clinical data, performance of the model, and their interpretation each make significant contributions to the predicted values. Although the overall R 2 value of 0.742 is not depicted on the figure, it supports the fact that the model accounts for a significant amount of variance. The visualization thereby supports the concept that multimodal transformer constructs have a considerable and positive effect on patient outcomes prediction (Meng et al., 2021).

DISCUSSION

The current research examined the opportunities of using multimodal transformer models to forecast pediatric cardiac arrest using both experimental data and sophisticated statistics. The results repeatedly point to the fact that the data is reliable, valid, and appropriate when it comes to testing hypotheses concerning the implementation of artificial intelligence (AI) in pediatric critical care. What is more important is that the findings offer empirical findings to the fact that the development of advanced multimodal models is not only possible but also effective in overcoming the drawbacks of the traditional clinical scoring tools like Pediatric Early Warning Score (PEWS) (Xu et al., 2023).

The test of normality supported that the data was distributed normally, which is especially important in that it verifies the applicability of the parametric methods of statistics. This makes the results of t-tests, ANOVA, regression, and correlation analyses sound and scientifically correct. The normal distribution of the responses also means that the perceptions of the participants were not strongly skewed, therefore, representing the results of a balanced and representative evaluation of multimodal AI usage in clinical settings. It is congruent with the previous research that the normal distribution in clinical data is crucial in improving the predictive modelling reliability in clinical practice (DeGroat et al., 2024).

The reliability test revealed high internal consistency of the questionnaire, where Cronbach's Alpha was 0.872. This implies that the survey instrument was an effective measure of clinical data integration, model performance, interpretability, ethical governance, clinical decision support adoption, patient safety, and technological readiness. Reliability of a high degree implies that the respondents are always in agreement with the theoretical constructs, hence lending credence to the tool. This observation is consistent with the literature available on the subject that highlights the need to adopt psychometric rigor in health technology adoption research studies so that the findings can be inferred to other clinical environments (Kyrollos et al., 2023).

The validity test also enhanced the strength of the research. The KMO value of 0.713 reported that there was enough sampling adequacy, and the Bartlett Test of Sphericity was significant ($p<0.05$), which confirmed that the data were fit to be analyzed through factor analysis. This validation shows that not only were the constructs measured internally consistent, but also theoretically consistent. Past research in the field of clinical informatics has also identified the necessity of construct validity in order to establish the relevance of the technological adoption frameworks in terms of the dimensions of perceptions that clinicians report as specific and relevant. The fact that the current findings show the research approach to be methodologically sound gives it an avenue to conduct confirmatory factor analysis in the future (Wang et al., 2023).

Comparison tests were conducted in groups, and as we could see, messages significantly differed between groups, which demonstrates the heterogeneity of perceptions between groups. The independent samples t-test revealed a significant difference between the two groups, which confirms that demographics or professional background can affect attitudes toward AI-driven cardiac arrest prediction. Likewise, ANOVA and Kruskal-Wallis tests revealed that there were significant differences in various groups, and the Chi-Square test revealed significant correlations between categorical responses. These results highlight the findings that adoption and perception of multimodal transformer models do not come across all stakeholders in the same way. As an example, doctors might be interested in interpretability and clinical utility, and data scientists might be more concerned with accuracy and model performance. The heterogeneity has been reflected in past research on the adoption of AI in healthcare, indicating that the implementation strategies should be different in various groups of users (Tan et al., 2024).

Correlation analysis indicated that there were consistently positive relationships between all constructs and moderate to strong associations. This implies that the enhancement of a particular area, like the integration of clinical data, is linked to the enhancement of others, like patient outcomes and interpretability. These findings can be empirically interpreted as robust empirical evidence of the conceptual coherence of multimodal transformer adoption in pediatrics. Notably, this supports the theoretical assumption that the use of AI is a multi-dimensional process, and it is necessary to align the technical possibilities, clinical trust, ethical protection, and organizational preparedness. Previous research on AI applications in cardiology and intensive care has also indicated that the successful implementation of predictive models is contingent on the concomitant reinforcement of a number of interrelated factors (Ding et al., 2024).

The regression analysis also highlighted that multimodal transformers were the most predictive, and the R 2 was 0.742, meaning that the independent variables accounted for almost three-quarters of the variation in the patient outcome measures. All coefficients were positive, indicating that clinical data integration, model performance, and interpretability have direct contributions to higher patient safety and outcomes. This result confirms the hypothesis of the present study: multimodal transformer models have great potential in predicting pediatric cardiac arrest. The findings align with the previous studies that indicated the effectiveness of AI-based multimodal systems in comparison with the conventional scoring systems with regard to identifying the presence of signs of decline at an early stage. The predictive power of such models is increased significantly by combining various types of data, such as vitals, lab values, imaging, and clinical narratives (Zhu et al., 2024).

In addition to being statistically validated, the results have significant clinical and ethical consequences. The reliability, validity, and predictability results are positive, which justifies the use of multimodal transformers in the decision support in pediatric intensive care units. Nevertheless, the considerable group differences highlight the need for stakeholder-specific training, communication, and policy development in order to guarantee successful adoption. Ethical protective measures, including the privacy of data and bias minimization in model predictions, are also of paramount concern. The high associations indicated by the correlations among the constructs also imply that the adoption of AI cannot be considered alone but as an overall change in terms of technological, clinical, and organizational systems (Liu et al., 2023).

Conclusion

This paper intends to investigate the reliability, validity, and predictive capacity of multimodal transformer models of early cardiac arrests in children. The results obtained through strict statistical tests proved that the data obtained were normative, highly reliable, and could be used in factor analysis. Excellent values of internal consistency were established by the Cronbach's Alpha value of 0.872, and the sufficiency and appropriateness of the data set were validated by the KMO and the Bartlett tests. All these findings showed that the research instrument was strong and instilled assurances with regard to the quality of the data.

Group comparison tests showed that there is a significant difference between the categories, which may indicate that the way AI-driven prediction is perceived differs among the stakeholders. This heterogeneity highlights the need to take into consideration the differences in demographics and professions in applying multimodal AI systems in clinical practice. The correlation analysis also indicated that such constructs as clinical data integration, model performance, interpretability, and patient safety have a positive association, which can emphasize the dependence of technical and organizational factors on each other.

Above all, regression analysis established that multimodal transformer models are highly predictive as they accounted for 74.2% of the variation in patient outcomes. The hypothesis that the AI-based multimodal integration can lead to significant improvement of prediction and better pediatric care results was confirmed by the positive coefficients of independent variables.

To summarize, this paper presents the transformative nature of multimodal transformer models as a promising future development of early warning systems to identify pediatric cardiac arrest. Although the diversity of stakeholders and the ethical protection measures, as well as the clinical preparedness, are crucial, the evidence shows a high degree of reliability and efficiency of the utilization of such models as a helpful and effective clinical decision-making support tool that could save lives.

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