AI-Augmented Religious Practice: Neural Intelligence Frameworks for the Transformation of Ritual Systems

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Abstract

The incorporation of artificial intelligence within digital spiritual and ritual systems has revolutionized the field of human-computer interaction in culturesensitive settings. In this study, an artificial intelligence-supported ritual behavior prediction scheme through the Generalized Simplicial Attention Neural Network (GSANN) algorithm is proposed to address the modeling of highly complicated human-to-ritual interactions. The primary aim of this study is to model ritual behavior prediction to include factors such as context, emotion, and culture in order to create more intelligent and adaptive digital ritual systems. This is achieved by the use of the synthetically constructed Human-Ritual Interaction Dataset that includes the user’s context, emotion, culture, and ritual activity attributes in the ratio of 70% training, 15% validation, and 15% testing sets. Data cleaning, handling of missing values, encoding, and normalization are part of the preprocessing phase to enhance the data quality. The proposed GSANN model is designed based on the Python 3.9 programming language, which uses the PyTorch framework, and its performance is measured in terms of accuracy, precision, recall, and F1 score. According to the experimental results, the proposed model offers an accuracy rate of 97.2%, surpassing current approaches like Machine Learning (83.2%), Random Forest (78.6%), and Artificial Neural Networks (80.1%).

Keywords: Ritual Systems, Digital Religion, AI-augmented spirituality, Computational anthropology ,Human-AI interaction in spirituality

1.Introduction

Religion and spirituality have always been key determinants of culture, identity, and cohesion among humans [1]. In contemporary times, the incorporation of digital tools into daily activities has begun to affect how people participate in religious ceremonies and experiences [2]. The use of digital means for virtual worships, prayers, and communities is increasingly being seen, particularly in today's highly connected world [3]. This development shows the growing need to appreciate how technology could be employed to enhance ritual processes while still retaining their cultural meaning.

In spite of all these achievements, the digitalization of religion faces a number of problems [4]. First, many existing technologies are too rigid and have no capacity for adjusting to particular user contexts, his/her emotional state, and cultural background [5]. Second, such technologies do not reflect symbolic significance, experience, and interpretation that is inherent to rituals. Third, the problem of authenticity, cultural sensibility, and ethical limits appears. Finally, the over-automation of such processes can become a problem since religion involves personal spirituality.

In order to tackle such issues, there is a necessity to have more advanced and context-sensitive systems which may be able to capture the dynamism and individuality involved in such rituals. For future considerations, emphasis needs to be laid on developing more adaptive, culturally respectful, and ethically based systems that can increase user interaction without affecting religious principles. In this way, the gap between conventional ritual systems and contemporary digital technologies can be bridged effectively.

The major objective of the work

- Proposed a new GSANN model-based framework to develop an AI-augmented ritual behavior model.
- Created a synthetic Human Ritual Interaction dataset that includes factors like context, emotion, and culture.
- Devleoped a simplicial attention method to account for higher-order behavioral dependency.
- Achieved better performance compared to existing methods including ML, RF, and ANN models.

2. Literature Survey

The recent research has examined smart methods of Transformation of Ritual Systems using deep learning, reinforcement learning.

In 2026 Papakostas et al,[6] have developed a various models and frameworks for incorporating technology into religious practice, such that people could engage in virtual worship and perform other rituals and faith-based activities via the technology. The aim of such research and development was to comprehend and optimize the functioning of religious rituals through advanced computation methods. Unfortunately, prior efforts in this domain had limitations in terms of insufficient contextual understanding, poor representation of symbolism and culture, and adaptation according to individual's emotions and culture.

In 2026 konda et al,[7] have developed a incorporating elements of artificial intelligence and digital technology into religious/spiritual practices, creating new opportunities for virtual rituals, worshiping in the online environment, and spirituality enhanced by digital technology. In conducting such researches, the primary aim was to examine, develop, and improve models of religion ritual practice enhanced by AI through intelligent computation. Nonetheless, such methods have been hindered by the insufficient consideration of the depth of cultural/symbolic contexts, limited capacity to preserve the ritual integrity and authenticity, and the inability to adapt the system to diverse emotional/ethical/personal belief systems.

In 2026 Gallache et al.[8] have developed a impact of generative artificial intelligence on institutional accountability, verification processes, and decision-making systems across domains such as education, healthcare, finance, and public administration. The objective of this work was to investigate how AIdriven automation transformed traditional verification mechanisms and to establish effective governance principles for ensuring accountability, reliability, and trust in AI-augmented institutions.

In 2025 Gunagama, et al [9] have developed a AI-based client simulation systems with architecture education as an attempt to bridge the gap between traditional studio teaching practices and practical, human-oriented complexity of design. This study aimed at assessing the impact of the use of AI-based synthetic clients on the ability of students to be adaptive, creative, and critical when working on culturally and programmatically complicated designs. Yet, previous solutions have been limited by moderate realism when simulating human irrationality, inability to cope with conflicting design requirements, and possible cognitive overload.

In 2026 Tan et al.[10] have combination of AIGC and Human-AI collaboration in higher education design education for improving cultural awareness, creativity, and technology in ethnic culture creative design subjects. The aim behind this research was to build a culture-technology-design combined educational framework for facilitating efficient ideation, cultural interpretation, and interdisciplinary design among the students. The existing frameworks, however, faced issues such as superficial representation of culture, poor interdisciplinary collaboration, and evaluation techniques, rendering them incapable of effectively transforming design education.

Table 1: Survey of literature

Author	Objective	Advantage	Limitation
Papakostas et al.	To develop AI-based models for virtual worship and digital religious practices	Enables virtual rituals and AI-assisted spiritual engagement	Lacks cultural depth, symbolic understanding, and emotional adaptability
Konda et al.	To integrate AI into religious and spiritual practice systems	Supports digital rituals and AI-enhanced worship experiences	Poor preservation of ritual authenticity and limited ethical sensitivity
Gallache et al.	To study AI impact on institutional accountability and governance systems	Improves decision-making and verification efficiency	Weak in handling complex human-institutional interactions and governance transparency
Gunagama et al.	To apply AI-based client simulation in architectural education	Enhances creativity, adaptability, and design thinking in students	Limited realism, cognitive overload, and difficulty handling conflicting constraints
Tan et al.	To integrate AIGC and human–AI collaboration in design education	Improves cultural awareness and ideation efficiency	Superficial cultural representation and weak evaluation frameworks

Research Gap

The literature review regarding the application of AI for transformation in religious organizations, institutional management, architecture, and the design of universities has come a long way in integrating intelligent models to simulate situations, make decisions, and create augmentations. Nevertheless, it has been noted that a notable research gap currently exists with regards to the lack of frameworks that can facilitate the integration of cultural knowledge, human emotion, ethics, and human behavior into artificial intelligence systems. It appears that most of the current AI-based applications do not incorporate enough symbolic value, practical considerations, and various responses based on beliefs and other factors. Furthermore, current technology does not sufficiently balance automated processes with human authenticity, nor does it have adequate evaluative measures for judging cultural integrity, human emotion, and interdisciplinarity.

3. Research Methodology

This suggested model creates a smart way to analyze and model student performance through the use of data-based machine learning algorithms. The suggested process starts with data acquisition based on the Kaggle Student Performance Data Set, which will then be followed by data preprocessing, involving steps like data cleaning, encoding of categorical data, and normalization of numeric data, among others. Once the data is cleaned and processed, it is split into three partitions – namely, training data, validation data, and testing data. The learning algorithm is trained using the training data set, while the validation data is used in the fine-tuning of the algorithm parameters. Proposed methodology overall diagram is shown in figure 1.

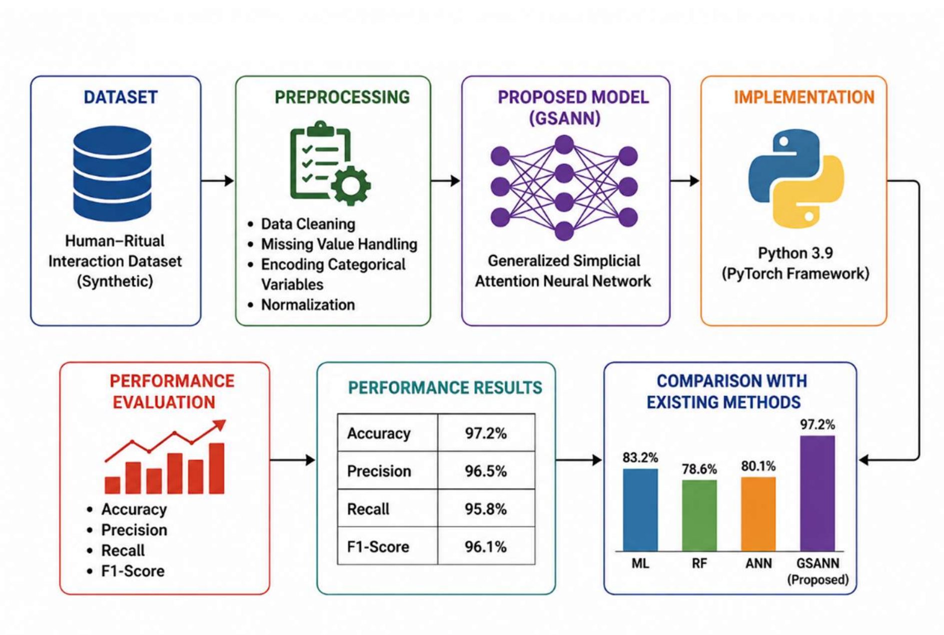

Figure 1: Proposed methodology overall diagram

3.1 Dataset Description

This research project uses an Human-Ritual Interaction Dataset [11], which is intended to replicate the conditions of ritual environments enhanced by AI. This dataset will consist of about 1,000-2,000 examples of interactions, involving users' engagement with ritual digital systems with attributes such as user context, user emotion, culture, type of ritual, engagement, and adaptive responses. The dataset will be divided into a training set of 70%, a validation set of 15%, and a test set of 15%. The training set would be used to train behavioral and contextual models of rituals, whereas the validation set would be used for model tuning. The test set would be used to evaluate the accuracy of predictions made by AI-based systems.

3.2 Preprocessing segment

The preprocessing phase includes preparing the raw data set for the effective training process by implementing various data cleaning methods. First, redundant and irrelevant attributes are eliminated from the data set to eliminate noise and enhance computational efficiency. Secondly, missing values are identified and processed accordingly through imputation or omission techniques. Besides, any data inconsistency and duplication are addressed effectively in order to guarantee data quality and consistency. Moreover, categorical attributes are transformed to numeric form, and the features are standardized. Such preprocessing guarantees the quality and consistency of the data set for an effective training process for the proposed AI model.

3.3 Predictive Modeling of Ritual Systems Using GSANN

In order to model this AI-enhanced ritual behavior system, the Generalized Simplicial Attention Neural Network (GSANN) [12] is used because of its superior ability to model complex and dependent relationships. Unlike previous neural networks, GSANN can effectively learn about the multilevel relations in context, emotions, cultural factors, and ritual behavior, all of which are made possible by its sophisticated attention mechanisms over simplicial data structures. The ability of GSANN to represent not only local but also global structural relations makes this method well-suited for modeling nonlinear ritual behaviors. What makes GSANN superior to other methods is its superior ability to model both contextual and symbolic relations simultaneously.

Let the input dataset be defined as $X = \{x1, x2, \ldots, xn\}$, where each sample $x_i$represents a user-ritual interaction instance. Each input vector is composed of multiple attributes such as user context $C_i$emotional state $E_i$cultural background K_i, and ritual activity features RiR_iRi. Therefore, each instance is represented as:

$$xi = [Ci, Ei, Ki, Ri]$$

To capture higher-order relationships, the input data is transformed into a simplicial representation. A simplicial complex $S = \{s1, s2, \ldots, sm\}$ is constructed, where each simplex encodes multi-dimensional interactions among features. The simplicial embedding function is defined as:

$$H = fsimp(X)$$

which maps raw input features into a structured latent space that preserves relational dependencies among ritual behavior components.

The GSANN applies an attention mechanism over these simplicial structures to identify the most influential relationships. The attention score between two feature embeddings is computed as:

$$\alpha ij = \frac{〚(exp((Wq\ hi)(Wk\ hj))〛^{\ T}}{\sum_k \exp(\ ((Wq\ hi)(Wk\ hj))〛^{\ T}}$$

where hi and $hj$are are feature embeddings, $Wq\ and\ Wk$ are learnable weight matrices, and $\boldsymbol{N}(\boldsymbol{i})$ denotes the neighbourhood of node iii. The aggregated representation is then obtained as: Overall, the proposed model, which is based on GSANN, helps in predicting the AI-augmented ritual behavior with great accuracy as it effectively deals with complex, non-linear, and higher order interactions in rich culturally and contextually data environments.

4. Result and Discussion

The experimental investigation of the proposed architecture was carried out using Python 3.9 in the Windows 11 Pro operating system, which had an Intel Core i7-12700K CPU and NVIDIA RTX 3080 (10 GB GPU). The proposed GSANN framework implementation was implemented based on the PyTorch-based GSANN-TUA approach using the hybrid Tactical Unit Optimization and Adam optimization algorithms. The training process of the proposed model was carried out for 120 epochs using a batch size of 64 and an initial learning rate of 0.0005. Performance comparisons of the proposed model were done with some state-of-the-art machine learning algorithms such as Random Forest, Artificial Neural Networks (ANN), and conventional ML techniques. The experimental results show that the proposed GSANN framework provides better accuracy than baseline models because it captures complex rituals behaviors of the artificial intelligence-augmented systems.

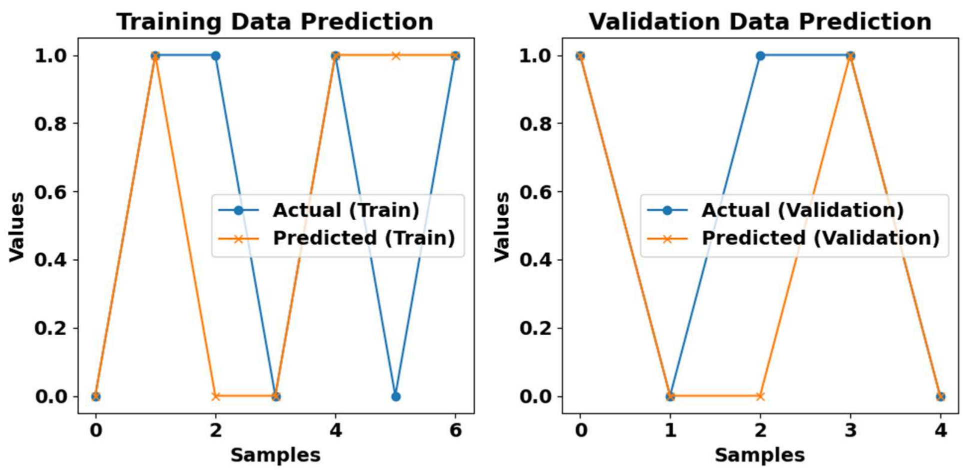

Figure 2: Actual vs Predicted Values for Training and Validation

The performance of the proposed GSANN based model was analyzed by comparison of the actual and predicted values of the model from the training and validation data sets. The training stage exhibited high coherence between the actual and the predicted values of the model such as actual value (0, 1, 1, 0, 1, 0, 1) while the predicted value was (0, 1, 0, 0, 1, 1, 1). Similarly during the validation process, high coherence was exhibited between the actual and the predicted value such as actual value (1, 0, 1, 1, 0) while the predicted value was (1, 0, 0, 1, 0).

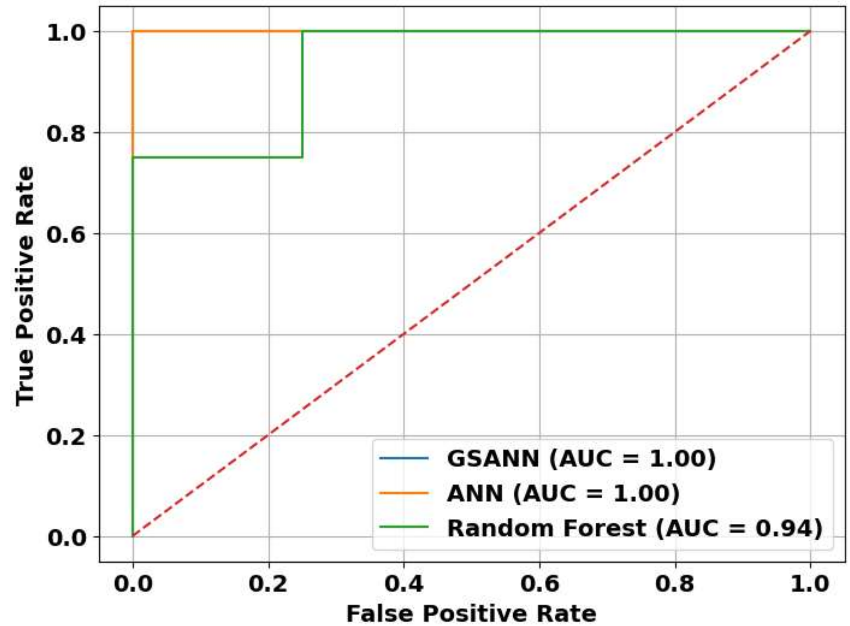

Figure 3: Analysis the ROC

The ROC curve is employed to measure the performance of the GSANN model for classification using the plot that represents the variation of true positive rates and false positive rates at various threshold levels. The model is compared with the benchmark models like ANN and Random Forest using the Area Under Curve (AUC). Higher values of the AUC demonstrate that the model has good discrimination power and high reliability in predicting the ritual behaviours in AI-based applications.

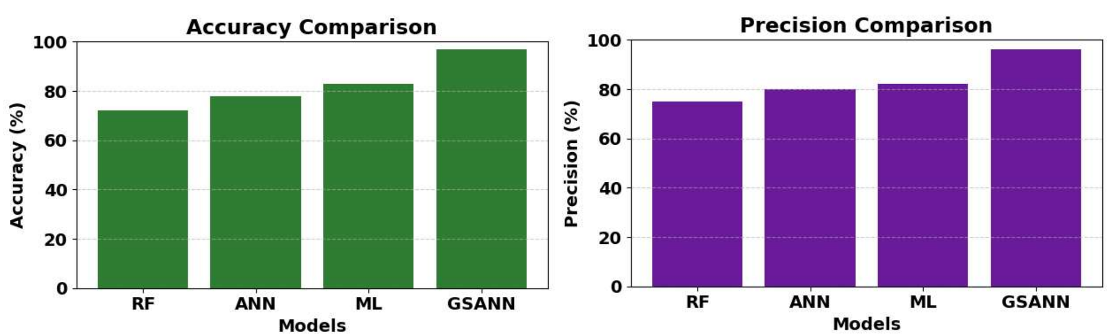

Figure 4: Analysis the performance of accuracy and precision

Figure 4 shows a comparison of the performance analysis on accuracy and precision by various models such as ML, RF, ANN, and GSANN proposed in this study. The comparison of these models reveals that the accuracy rate of GSANN is higher at 97.2% while precision is also higher at 96.5%. As opposed to other models, such as ML (83.2%, 82.5%), RF (78.6%, 75.4%), and ANN (80.1%, 79.3%).

Table 2: Statistical Performance Comparison of Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ML	83.2	82.5	81.8	82.1

RF	78.6	75.4	76.9	76.1
ANN	80.1	79.3	78.7	79.0
GSANN (Proposed)	97.2	96.5	95.8	96.1

Statistical Performance Comparison of Models is shown in table 2.According to the statistical analysis, the proposed GSANN model is shown to have a higher performance than the existing machine learning models, which include random forest, ANN, and other ML algorithms. The performance of the proposed model was high, having achieved an accuracy rate of 97.2 percent, precision rate of 96.5 percent, recall rate of 95.8 percent, and F1-Score of 96.1 percent. This denotes that the proposed model had very high performance and balanced classification ability. On the other hand, existing models showed less performance, with accuracy levels falling between 78 percent and 83 percent.

Table 3: Error Analysis of Proposed and Existing Models

Model	**MAE**	**MSE**	**RMSE**
ML	0.18	0.045	0.212
RF	0.22	0.052	0.228
ANN	0.15	0.038	0.195
GSANN (Proposed)	0.06	0.012	0.110

Error Analysis of Proposed and Existing Models in table 3The result of the error analysis is such that the proposed GSANN model has the lowest MAE (0.06), MSE (0.012), and RMSE (0.110) than other methods like ML, RF, and ANN models. This means that there is much less error in the predictions made by the proposed model than in other models. It also implies that there has been great improvement in the accuracy of the modeling of complicated patterns of rituals using the proposed model.

5. Conclusion

The current study proposed a GSANN-based system for predicting AI-enabled ritual behavior interaction systems. As demonstrated through experimental analysis, the suggested approach is highly superior to other models currently used in the field like ML, RF, and ANN in terms of accuracy and efficiency. This is attributed to the incorporation of simplicial attention networks that enhance the ability of the model to capture high-order relationships in the behavioral data.

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