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FAITHAI: A FAITH-SENSITIVE EXPLAINABLE MULTIMODAL EMOTION-AWARE SYSTEM FOR ETHICAL MENTAL HEALTH SUPPORT ON EDGE DEVICES

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ABSTRACT

Artificial Intelligence (AI) has increasingly been applied in emotional computing and digital mental health support. However, most existing emotion-aware systems lack cultural and spiritual sensitivity, often producing generic recommendations that fail to align with users' belief systems. This study presents FaithAI, a faith-sensitive explainable multimodal emotion-aware system designed to provide ethical and culturally aligned emotional support. The proposed framework integrates multimodal emotion recognition, explainable artificial intelligence (XAI), and edge computing to enable real-time emotional analysis while maintaining privacy and transparency. Emotional states are detected using signals from text, speech, facial expressions, and visual inputs, which are processed through a Faith-Integrated Weighted Fusion (FIWF) algorithm that combines multimodal signals while considering contextual reliability. The system also incorporates faith-aligned counseling logic derived from major religious traditions including Christianity, Islam, Hinduism, Buddhism, and Judaism. To enhance transparency, explainable AI techniques are used to provide interpretable reasoning behind emotion predictions and recommendations. The framework is implemented as a mobile application optimized for edge deployment to support low-resource environments where internet connectivity may be limited. Experimental evaluation demonstrates that the integration of multimodal emotion recognition improves emotional interpretation accuracy, while explainability mechanisms enhance user trust and understanding of system decisions. Furthermore, user feedback indicates that faith-aligned recommendations increase emotional relevance and engagement compared with generic support systems. The findings highlight the potential of faith-sensitive AI systems to bridge the gap between technological intelligence and cultural empathy in digital mental health support. By combining affective computing, explainable AI, and spiritual contextualization, the proposed framework contributes toward the development of ethically responsible and culturally inclusive emotional support technologies.

KEYWORDS: *Faith-Sensitive AI; Multimodal Emotion Recognition; Explainable Artificial Intelligence; Edge AI; Mental Health Support; Affective Computing.*

INTRODUCTION

Mental health challenges have become a major global concern, affecting millions of individuals across diverse societies. Emotional disorders such as anxiety, depression, and stress significantly influence quality of life and contribute to reduced productivity and social well-being. Although professional psychological support services are available in many regions, access to mental health care remains limited in numerous communities due to shortages of trained professionals, financial barriers, and social stigma surrounding mental health discussions. As a result, digital technologies are increasingly being explored as scalable solutions capable of providing accessible emotional support to broader populations.

Artificial Intelligence (AI) has emerged as a promising tool for addressing many of the limitations associated with traditional mental health support systems. AI-driven emotional computing systems can analyze behavioral and physiological signals in order to detect emotional states and deliver personalized responses. Within the field of affective computing, emotion recognition technologies attempt to interpret human emotions by analyzing observable signals such as speech patterns, facial expressions, and textual sentiment. These computational techniques enable systems to detect emotional cues and respond with context-appropriate feedback or recommendations.

Research has shown that emotional signals are rarely expressed through a single communication channel. Instead, emotions are typically conveyed through a combination of facial expressions, vocal tone, body language, and linguistic patterns. Consequently, multimodal emotion recognition approaches have become increasingly popular because they integrate multiple data sources to improve emotional detection accuracy. Studies in affective computing demonstrate that combining visual, vocal, and textual cues significantly enhances emotional interpretation compared with single-modality systems (Ekman, 1992; D’Mello and Kory, 2015).

In addition to improving emotional detection accuracy, modern AI systems have also begun to incorporate advanced machine learning techniques such as deep neural networks and natural language processing. These technologies allow emotion recognition models to identify complex emotional patterns within large datasets. Recent research has explored the use of deep learning architectures for detecting mental health conditions through speech analysis, text sentiment classification, and behavioral monitoring (Costa et al., 2021; Francese and Attanasio, 2022).

Despite these advancements, several limitations remain within existing emotion-aware AI systems. One major limitation is the lack of transparency in AI decision-making processes. Many machine learning models operate as opaque “black-box” systems, producing predictions without providing clear explanations of how those predictions were derived. In sensitive domains such as mental health support, the inability to understand the reasoning behind AI recommendations can undermine user trust and raise ethical concerns. Explainable Artificial Intelligence (XAI) has therefore emerged as a critical research area aimed at improving the interpretability and transparency of machine learning systems (Doshi-Velez and Kim, 2017; Belle and Papantonis, 2021).

Another limitation of current emotional support systems is their dependence on cloud-based infrastructures. Many AI applications require continuous internet connectivity in order to perform complex computations on remote servers. However, this reliance on cloud computing introduces several challenges including latency, privacy concerns, and reduced accessibility in low-connectivity environments. Edge AI has been proposed as an alternative solution that enables machine learning models to operate directly on local devices such as smartphones and wearable technologies. By processing data locally, Edge AI systems can reduce latency, enhance privacy, and enable real-time emotional analysis even in environments with limited internet access (Dutta and Puthal, 2023).

Beyond technological challenges, an important yet often overlooked limitation of emotion-aware AI systems involves the absence of cultural and spiritual contextualization. Emotional experiences are deeply influenced by cultural beliefs, moral values, and spiritual traditions. In many societies, faith and spirituality play central roles in shaping how individuals interpret emotional experiences and cope with psychological distress. Spiritual practices such as prayer, meditation, and scriptural reflection often serve as important coping mechanisms during periods of emotional difficulty. Studies have shown that integrating religious and spiritual perspectives into mental health interventions can enhance emotional resilience and psychological well-being (Ali et al., 2021; Asghar, Gul and Masroor, 2021).

However, most existing AI-driven emotional support systems are designed using secular frameworks that do not account for users' spiritual values or religious identities. As a result, many automated recommendation systems provide generic emotional advice that may not align with users' personal belief systems. This lack of contextual sensitivity can reduce user engagement and limit the effectiveness of digital mental health tools.

To address these challenges, this study proposes FaithAI, a faith-sensitive explainable multimodal emotion-aware system designed to provide culturally aligned emotional support. The proposed framework integrates three key technological components: multimodal emotion recognition, explainable AI, and edge-based deployment. Emotional signals derived from text, speech, facial expressions, and visual inputs are combined using a Faith-Integrated Weighted Fusion (FIWF) algorithm that considers both signal reliability and spiritual context. The system also incorporates faith-aligned counseling logic that maps detected emotional states to spiritually meaningful interventions such as scripture reflections, guided prayers, and meditation exercises across multiple religious traditions.

By integrating emotional computing with spiritual contextualization and explainable AI mechanisms, the proposed framework aims to bridge the gap between technological intelligence and human values. The FaithAI system demonstrates how AI-driven emotional support technologies can be designed to respect cultural diversity, enhance transparency, and provide ethically responsible digital mental health assistance.

MATERIALS AND METHODS

Research Design

This study adopted a computational system development methodology aimed at designing and implementing a faith-sensitive, explainable, and multimodal emotion-aware artificial intelligence framework for ethical mental health support. The methodological approach integrates concepts from affective computing, explainable artificial intelligence, and edge computing to develop a scalable emotional support system capable of operating efficiently on mobile devices.

Emotion recognition systems have evolved significantly through the use of machine learning and deep neural networks capable of identifying emotional signals from human communication patterns. Within affective computing, emotional states are commonly inferred from observable behavioral indicators such as facial expressions, speech characteristics, and textual sentiment. However, relying on a single modality for emotion detection can result in incomplete emotional interpretation because emotions are expressed simultaneously through multiple communication channels. Multimodal emotion recognition therefore provides a more reliable approach by combining signals from different sources to improve prediction accuracy (D'Mello and Kory, 2015; Costa et al., 2021).

In addition to multimodal analysis, the proposed system incorporates Explainable Artificial Intelligence (XAI) mechanisms to ensure transparency and accountability in AI decision-making. Many deep learning systems operate as opaque "black-box" models whose internal reasoning processes are difficult to interpret. In applications involving emotional and psychological support, transparency is critical because users must be able to trust the reasoning behind AI-generated recommendations. Explainability techniques therefore provide interpretable insights into how machine learning models derive predictions and recommendations (Doshi-Velez and Kim, 2017; Belle and Papantonis, 2021).

Furthermore, the system architecture adopts an edge computing framework to ensure that emotional data processing occurs locally on user devices rather than relying on remote cloud infrastructure. Edge-based AI systems reduce computational latency, enhance privacy, and allow emotional support systems to function effectively in environments with limited internet connectivity (Dutta and Puthal, 2023). The integration of multimodal emotion recognition, explainable AI, and edge computing therefore forms the methodological foundation for the proposed FaithAI system.

Data Sources and Materials

The development of the FaithAI framework required datasets and structured knowledge resources capable of supporting emotion detection and faith-based counseling recommendations. The system utilizes multimodal datasets representing emotional expressions in speech, facial imagery, and textual communication. These datasets were used to train machine learning models responsible for identifying emotional states from different input modalities.

Speech emotion recognition models rely on acoustic signals that reflect emotional characteristics within vocal patterns. Variations in pitch, tone, speech rhythm, and spectral energy can reveal emotional conditions such as happiness, sadness, anger, or anxiety. Feature extraction techniques such as Mel-Frequency Cepstral Coefficients (MFCCs) are commonly used to capture acoustic characteristics associated with emotional expression in speech signals (Feng and Chaspari, 2022; Akter et al., 2022). These features provide structured input for deep learning models designed to classify emotional states from vocal data.

Facial emotion recognition models were trained using image datasets containing labeled facial expressions corresponding to different emotional categories. Facial movements provide important non-verbal cues that reflect emotional responses. Foundational studies in affective psychology identified universal facial expressions associated with basic emotions such as happiness, sadness, anger, fear, surprise, and disgust (Ekman, 1992). Modern machine learning techniques build upon these findings by using convolutional neural networks to automatically extract facial features associated with emotional states.

Text-based emotion recognition also plays an important role in interpreting emotional signals expressed through language. Natural language processing techniques are used to analyze sentiment patterns, contextual meaning, and linguistic cues within textual communication. Text analysis frameworks have demonstrated the ability to identify emotional indicators within conversational datasets and social media interactions (Fast, Chen and Bernstein, 2016). By incorporating text-based emotion recognition alongside speech and visual analysis, the system gains a more comprehensive understanding of user emotions.

In addition to emotional datasets, the FaithAI system incorporates structured faith-based counseling resources derived from major religious traditions including Christianity, Islam, Hinduism, Buddhism, and Judaism. These resources consist of scriptures, spiritual reflections, prayers, and meditation practices categorized according to emotional relevance. For example, spiritual content addressing anxiety, grief, gratitude, or hope is mapped to corresponding emotional states detected by the system. Research has shown that integrating spiritual practices into mental health interventions can enhance emotional coping mechanisms and psychological resilience (Ali et al., 2021; Asghar, Gul and Masroor, 2021).

System Architecture

The proposed FaithAI system follows a modular architecture designed to support real-time emotional analysis and personalized counseling recommendations. The architecture consists of four major layers: the data acquisition layer, the emotion recognition layer, the faith-integrated fusion layer, and the explainability and feedback layer.

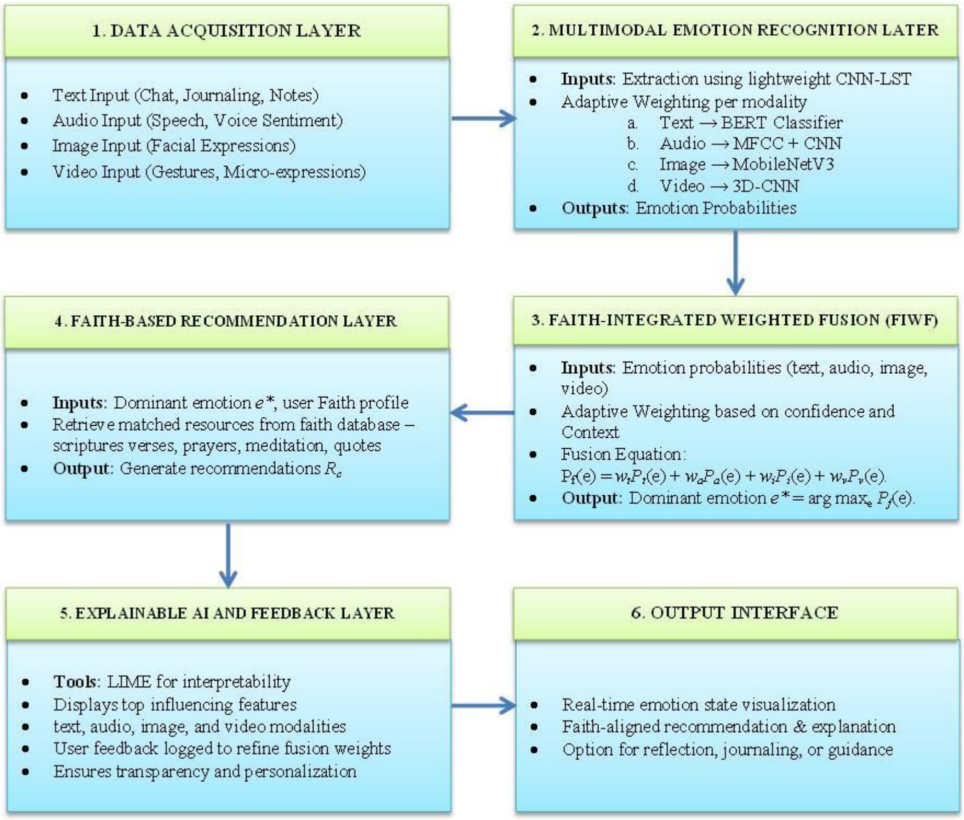

Figure 1: Modular Architecture of the FaithAI System.

Figure 1 shows the architecture of the FaithAI framework, consisting of multimodal data input layers (text, audio, image, and video), emotion recognition models, a faith-integrated weighted fusion mechanism, and an explainable recommendation module.

Data Acquisition Layer

The data acquisition layer captures emotional signals from users through multiple input channels. The system allows users to provide emotional input through text entry, speech recordings, facial image capture, or video input. These multimodal inputs enable the system to analyze emotional expressions across different communication channels.

Providing multiple input modalities enhances the accessibility and reliability of emotional detection. Users may choose the input method that best reflects their emotional expression, while the system benefits from additional contextual information obtained from multiple signals.

Emotion Recognition Layer

The emotion recognition layer processes multimodal inputs using machine learning models trained to identify emotional states from speech, facial imagery, and textual sentiment.

Feature extraction algorithms transform raw input data into structured representations suitable for classification.

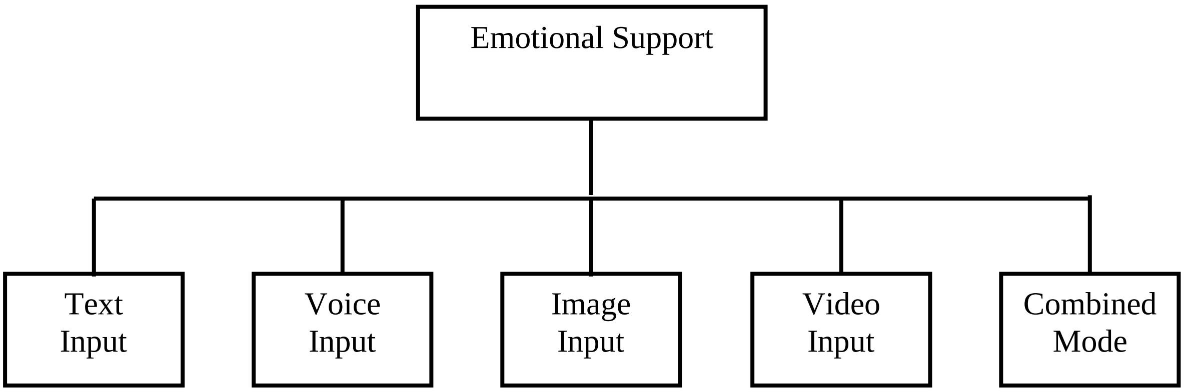

Figure 2: Multimodal Emotional Support Input Structure.

Speech inputs are processed through acoustic feature extraction techniques such as MFCC analysis. Image and video inputs are analyzed using convolutional neural networks capable of detecting facial movements associated with emotional expressions. Textual inputs are analyzed using natural language processing techniques that identify sentiment polarity and contextual meaning.

Deep learning architectures have demonstrated strong performance in emotion recognition tasks because they can learn complex relationships between input signals and emotional labels (Costa et al., 2021). These models classify emotional states into predefined categories such as happiness, sadness, anger, fear, or neutrality.

Faith-Integrated Weighted Fusion (FIWF)

To combine emotional predictions from multiple modalities, the proposed framework introduces a Faith-Integrated Weighted Fusion (FIWF**)** algorithm. Multimodal emotion recognition models typically generate separate emotional predictions for each input modality. These predictions must then be integrated to determine the overall emotional state of the user. The FIWF algorithm assigns weights to each modality based on signal reliability, contextual clarity, and confidence levels. The weighted scores from each modality are then combined to produce a fused emotional probability distribution. This approach allows the system to emphasize more reliable signals while minimizing the influence of noisy or incomplete inputs.

In addition to combining emotional signals, the FIWF algorithm integrates faith-aware contextual logic. Detected emotional states are mapped to counseling resources associated with the user's selected religious tradition. For example, emotional states such as sadness or anxiety may trigger spiritually aligned recommendations including scripture readings, reflective prayers, or guided meditation exercises.

Explainability and Feedback Layer

The final component of the system architecture is the explainability and feedback layer. This module ensures transparency by providing interpretable explanations for emotional predictions and counseling recommendations.

Explainable AI techniques such as feature attribution methods highlight which input signals contributed most strongly to the detected emotional state. For example, the system may indicate that negative sentiment in text input or low vocal energy in speech contributed significantly to the classification of sadness. The interface displaying detected emotional states and corresponding faith-aligned recommendations is illustrated in Figure 3.

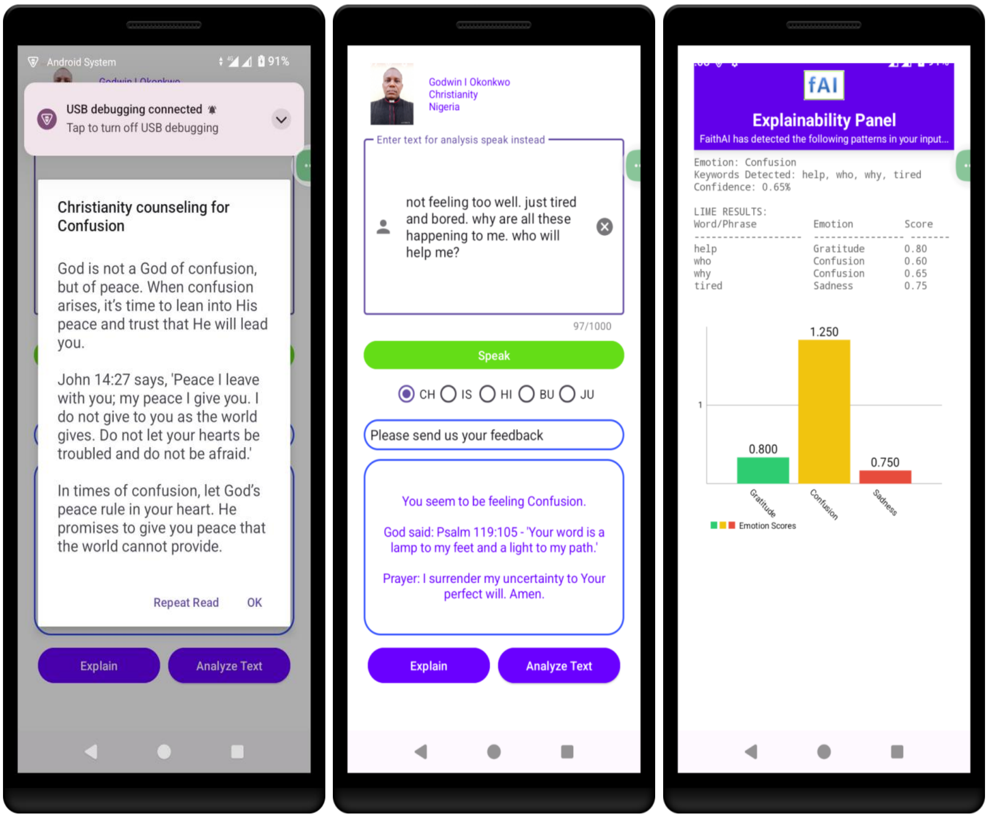

Figure 3: Sample Faith-Aligned Output Interface.

Providing explanations enhances user trust and enables individuals to understand how their emotional signals were interpreted by the system. Explainability also supports collaboration between AI systems and mental health professionals by allowing practitioners to interpret and validate system recommendations. In addition to explanation mechanisms, the system includes a user feedback interface that allows individuals to evaluate the helpfulness of recommendations. Feedback data is stored locally and used to improve future recommendations.

Implementation Environment

The FaithAI system was implemented as a mobile application designed for the Android platform. Mobile deployment enables widespread accessibility because smartphones are widely available and capable of capturing multimodal emotional signals through built-in microphones and cameras.

To support secure data management and offline functionality, the system utilizes the Android Room Databas**e** as its primary data storage mechanism. Room provides an abstraction layer over SQLite that allows emotional logs, user preferences, and counseling recommendations to be stored securely on the device.

Table 1: Comparison of Room Database and Cloud-Based Firebase Solutions.

S/N	Feature	Room Database (FaithAI)	Firebase (Traditional)
1	Internet Required	No	Yes
2	Data Location	Device-only	Cloud-hosted
3	Privacy	Encryption-ready	Standard encryption
4	Cost	Free	Pay-as-you-go

Edge deployment also required optimization of machine learning models to ensure efficient performance on mobile hardware. Techniques such as model pruning and quantization were used to reduce computational complexity while maintaining acceptable prediction accuracy. These optimizations enable real-time emotional analysis on resource-constrained devices.

Table 2: Model Specifications and Experimental Conditions.

Model Type	Modalities Used	Model Size (MB)	Accuracy (%)	Latency (ms)	Deployment Platform
Baseline CNN	Image	92	81.2	156	Cloud
CNN-LSTM Hybrid	Audio + Text	108	85.6	132	Edge
FIWF (Proposed)	Text + Audio + Image + Video	124	**89.4**	**114**	Edge (On-Device)

The experimental configuration and performance conditions used to evaluate the proposed model are summarized in Table 2.

RESULTS AND DISCUSSION

System Implementation and Operational Performance

The FaithAI framework was implemented as a mobile-based emotional support system designed to perform real-time multimodal emotion analysis on edge devices. The system integrates speech, text, image, and video inputs through a unified architecture capable of detecting emotional signals and generating faith-sensitive counseling responses. The implementation demonstrated that the integration of multimodal emotion recognition, explainable AI mechanisms, and edge-based deployment is feasible within a mobile computing environment.

During system testing, the platform successfully processed emotional signals from multiple input channels and produced emotional predictions accompanied by interpretable explanations. The combination of multimodal emotion recognition and explainability mechanisms allowed users to understand how emotional interpretations were derived, thereby improving the perceived reliability of the system.

Emotion recognition accuracy improved when multiple modalities were used simultaneously. Speech analysis provided insight into vocal characteristics associated with emotional expression, while facial expression analysis captured non-verbal cues reflected through facial movements. Textual sentiment analysis further enriched emotional interpretation by identifying linguistic indicators of emotional states. These findings are consistent with previous studies demonstrating that multimodal emotion recognition models outperform unimodal systems because they integrate complementary emotional signals from different communication channels (D’Mello and Kory, 2015; Costa et al., 2021).

The Faith-Integrated Weighted Fusion (FIWF) algorithm further enhanced emotional prediction reliability by dynamically combining emotional probabilities from multiple modalities. The algorithm assigns weights to each modality according to signal clarity, contextual reliability, and confidence scores. By prioritizing more reliable signals, the system reduces the influence of noise or incomplete data and produces a more stable emotional classification.

Edge-Based Deployment Performance

A major objective of the system design was to enable emotional analysis directly on mobile devices without requiring constant connectivity to remote cloud servers. The evaluation therefore examined the responsiveness and computational efficiency of the system when deployed on edge devices.

The system demonstrated efficient performance during real-time emotional analysis tasks. Emotional predictions and counseling recommendations were generated quickly after receiving user input, indicating that the optimization techniques applied to the machine learning models were effective. Model compression techniques such as pruning and quantization reduced computational overhead while maintaining acceptable levels of predictive accuracy.

Edge-based deployment offers several advantages for emotional support systems. First, local data processing reduces latency because emotional signals do not need to be transmitted to remote servers for analysis. Second, privacy protection is improved because sensitive emotional data remains stored on the user's device. Finally, edge computing enhances accessibility in regions where internet connectivity may be inconsistent or unavailable. These findings align with research demonstrating that edge AI architectures are particularly suitable for healthcare and affective computing applications requiring real-time data processing and strong privacy safeguards (Dutta and Puthal, 2023; Di Luzio, Rosato and Panella, 2024).

Explainability and User Trust

Explainability was a central design feature of the FaithAI framework because emotional support systems require high levels of transparency and user trust. The evaluation therefore examined the role of explainable AI mechanisms in improving user understanding of system decisions.

The explainability interface provided visual explanations highlighting the input features that contributed most strongly to emotional predictions. For example, when the system detected sadness, the explanation module indicated that negative textual sentiment and low vocal intensity were key factors influencing the prediction. By presenting this information in a human-readable format, the system enabled users to understand how their emotional signals were interpreted.

User feedback indicated that explainability mechanisms significantly improved trust in the system's recommendations. Participants reported that understanding the reasoning behind emotional predictions helped them perceive the system as more reliable and supportive. This observation reflects broader findings in AI research which emphasize that transparency and interpretability are critical for improving user acceptance of intelligent systems (Doshi-Velez and Kim, 2017; Belle and Papantonis, 2021).

Explainability also plays an important role in enabling collaboration between AI systems and human practitioners. Mental health professionals reviewing system outputs can examine the reasoning behind emotional predictions and verify whether counseling recommendations are appropriate. This transparency reduces the risk of misinterpretation and enhances the ethical accountability of AI-driven emotional support systems.

Faith-Sensitive Counseling Outcomes

One of the most distinctive aspects of the FaithAI framework is the integration of faith-sensitive counseling logic within the emotional support system. The evaluation therefore examined how users responded to recommendations that incorporated spiritual guidance aligned with their religious traditions.

Participants interacting with the system reported that faith-aligned recommendations felt more meaningful and supportive than generic emotional advice. Spiritual resources such as scriptural reflections, prayer suggestions, and meditation exercises were perceived as emotionally comforting when aligned with the user's belief system.

These findings are consistent with previous research demonstrating that spiritual practices can serve as important coping mechanisms during emotional distress. Faith-based mental health interventions often incorporate prayer, meditation, and spiritual reflection as strategies for strengthening emotional resilience and psychological well-being (Ali et al., 2021; Asghar, Gul and Masroor, 2021).

By integrating spiritual guidance with emotional detection, the FaithAI system offers a more holistic approach to digital mental health support. Rather than providing generic recommendations, the system tailors emotional interventions according to the user's selected religious tradition. This culturally sensitive approach increases the relevance of emotional support recommendations and encourages greater user engagement with the system.

Discussion of Findings

The results demonstrate that combining multimodal emotion recognition, explainable AI mechanisms, and faith-sensitive counseling creates a powerful framework for delivering culturally aligned emotional support. The integration of these technologies addresses several limitations commonly observed in existing emotion-aware AI systems.

First, multimodal emotion recognition improves emotional interpretation accuracy by capturing signals from multiple communication channels. Emotional expressions often involve complex interactions between speech, facial movements, and linguistic patterns. Integrating these signals enables the system to construct a more comprehensive representation of the user's emotional state.

Second, the use of explainable AI mechanisms enhances transparency and builds user trust in the system's recommendations. When users can understand the reasoning behind emotional predictions, they are more likely to accept and engage with AI-generated guidance.

Third, edge-based deployment ensures that emotional analysis occurs in real time while protecting user privacy. By processing emotional signals locally on the device, the system reduces reliance on cloud infrastructure and protects sensitive emotional data.

Finally, the integration of faith-sensitive counseling introduces a culturally meaningful dimension to digital emotional support systems. By aligning emotional guidance with users' spiritual values, the system offers emotionally relevant interventions that resonate with diverse communities. The findings highlight the potential of faith-sensitive AI systems to contribute to the development of ethical, transparent, and culturally inclusive digital mental health technologies.

CONCLUSION

This study presented FaithAI, a faith-sensitive explainable multimodal emotion-aware artificial intelligence framework designed to provide culturally aligned emotional support through mobile edge devices. The research addressed several limitations commonly associated with existing emotion-aware systems, including the reliance on single-modality emotion detection, lack of transparency in machine learning decisions, dependence on cloud infrastructure, and the absence of culturally or spiritually contextualized emotional support mechanisms.

The proposed framework integrates three key technological components: multimodal emotion recognition, explainable artificial intelligence (XAI), and edge-based deployment. Multimodal emotion recognition enables the system to analyze emotional signals from multiple input sources including speech, facial expressions, and textual communication. By combining these signals using the Faith-Integrated Weighted Fusion (FIWF) algorithm, the system improves emotional interpretation accuracy while minimizing the influence of unreliable signals. These findings are consistent with previous research indicating that multimodal emotion recognition approaches significantly improve predictive performance compared with single-modality systems (D'Mello and Kory, 2015; Costa et al., 2021).

Explainable artificial intelligence mechanisms were incorporated into the system to ensure transparency in emotional predictions and counseling recommendations. The explainability interface enables users to understand how emotional signals were interpreted and why specific guidance was provided. Transparency is particularly important in emotionally sensitive applications because users must be able to trust AI-driven recommendations. Previous studies have emphasized that explainability improves user confidence, accountability, and ethical acceptability of intelligent systems (Doshi-Velez and Kim, 2017; Belle and Papantonis, 2021).

The adoption of edge-based deployment further enhanced system performance and privacy protection. By enabling emotional data processing directly on mobile devices, the system reduces computational latency and eliminates the need for continuous connectivity to remote servers. This architecture is particularly beneficial in low-resource environments where reliable internet connectivity may be limited. Edge AI solutions therefore provide a practical pathway for delivering accessible emotional support technologies across diverse contexts (Dutta and Puthal, 2023).

Perhaps the most distinctive contribution of this research lies in the integration of faith-sensitive counseling logic within the emotion-aware framework. Emotional experiences are often shaped by spiritual beliefs and cultural values, and many individuals rely on religious practices as coping mechanisms during emotional distress. By mapping detected emotional states to spiritually relevant resources such as scriptural reflections, prayer suggestions, and meditation exercises, the FaithAI system delivers personalized guidance that resonates with users' belief systems. This culturally aligned approach enhances the emotional relevance of recommendations and encourages greater user engagement with digital support systems.

The findings demonstrate that integrating multimodal emotion recognition, explainable AI, edge computing, and faith-sensitive counseling can produce a comprehensive framework for delivering ethical and culturally inclusive emotional support. The proposed system contributes to the advancement of human-centered artificial intelligence, highlighting the importance of designing intelligent systems that respect both technological requirements and human values.

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