Volume 2, 2026, Pages 53-66 *Elaris Computing Nexus*
| Regular Article | Open Access

Cross Modal Explainable Intelligence Architecture for Resource Aware Decision Optimization in Adaptive Computing Systems

Arulmurugan Ramu
Computer Science and Software Engineering, Heriot-Watt University (Zhubanov Campus), Aktobe, Kazakhstan.
a.ramu@hw.ac.uk

Anandakumar Haldorai
Department of Computer Science and Engineering, Sri Eshwar College of Engineering, Coimbatore, India.
anandakumar.h@sece.ac.in

Article Info
Elaris Computing Nexus
https://elarispublications.com/journals/ecn/ecn_home.html

Received 23 January 2026
Revised from 24 March 2026
Accepted 30 March 2026
Available online 06 April 2026

© The Author(s), 2026.

https://doi.org/10.65148/ECN/2026005
Published by Elaris Publications.

Corresponding author(s):
Anandakumar Haldorai, Department of Computer Science and Engineering, Sri Eshwar College of Engineering, Coimbatore, India.
Email: anandakumar.h@sece.ac.in

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

Abstract – With the growing diversity of adaptive computing systems, there is a need for intelligent decision-making mechanisms that must optimize resource utilization, computation efficiency and maintain model transparency. However, most of the existing resource-aware optimization approaches do not consider cross-modal information integration and explainability, and thus cannot be applied to dynamic and constrained computing scenarios. In order to address these challenges, this paper presents an architecture for Cross-Modal Explainable Intelligence (CMEIA) for the Resource-Aware Decision Optimization in Adaptive Computing Systems. The proposed architecture involves the adaptive cross-modal fusion framework and the explainable intelligence module, which are used to fuse multimodal inputs and give transparent and interpretable decision pathways, respectively. A dynamic resource management engine continually adjusts the allocation of computational resources to meet contextual awareness, workload characteristics and system constraints, thereby allowing scalable and adaptive decision optimization. Unlike the traditional method which separately optimizes the resource and explains the model, the proposed model addresses all the three aspects of performance, explainability, and adaptability at the same time. Decision accuracy, utilization efficiency of resources, computational latency, energy consumption, throughput, scalability, fidelity of explanations, and level of confidence in decisions under different workloads are some of the critical performance parameters used to measure the effectiveness of CMEIA. An experimental assessment shows that the developed architecture optimizes the resources in a way that is superior, while simultaneously ensuring high levels of explainability and adaptability in heterogeneous computing environments. This framework is being used to greatly boost intelligent decision making, increase computational efficiency and yield transparent and trustworthy optimization strategies for next generation adaptive computing environments.

Keywords – Cross-Modal Explainable Intelligence, Resource-Aware Decision Optimization, Adaptive Computing Systems, Multimodal Data Fusion, Explainable Artificial Intelligence (XAI), Dynamic Resource Management.

I. INTRODUCTION

In today's technologically advanced landscape, adaptive computing systems have proven to be an essential part of intelligent infrastructures, facilitating dynamic resource allocation and context-aware decision-making in various computational settings. These systems receive and process heterogeneous data streams continuously under challenging constraints of latency, energy consumption, large scale and computation efficiency, and span across edge-cloud ecosystems, autonomous cyber-physical platforms, and intelligent healthcare and industrial automation. An increased adoption of multimodal sensing technologies has further heightened the demand for architectures that can integrate multiple (textual, visual, temporal, and system-level operational) cross-modal information from multiple sources. Thus, resource-aware optimization is essential to attain intelligent and sustainable computing performances in dynamic environments [1]. Existing AI solutions are mostly focused on performance optimization with limited explainable and transparent decision-making capabilities, although there have been great strides in adaptive intelligence. Many AI models are black box, and this lack of transparency and accountability of how an AI model works can hinder the adoption of AI in mission critical applications where interpretability, accountability and trustworthiness are crucial. Moreover, resource limitation in adaptive computing environments requires intelligent optimization techniques that not only enhance the overall performance of the computing environment but also efficiently use the computational resources. These challenges require to create cross-modal explainable architectures that can not only optimize the allocation of resources but also enhance the quality of decisions and offer interpretable insights into the underlying decision-making process [2].

Evolution of Resource-Aware Adaptive Computing Systems

Artificial intelligence, distributed computing and heterogeneous processing paradigms have caused significant changes in adaptive computing systems. The traditional approaches to resource management were mainly based on static allocation policies, which were not suitable for dynamically varying workloads and contexts. In modern adaptive systems, intelligent optimization methods are used more and more to improve the efficiency of the computation without compromising the responsiveness of the system [3].

With the explosion of multimodal data comes new opportunities and challenges to adaptive decision optimization. Cross-modal intelligence allows computational models to harness complementary information across multiple data modalities, leading to enhanced robustness, context understanding and predictive performance. However, the inclusion of heterogeneous information sources is a difficult task because of the modality-specific representations, the need for synchronisation requirements and limited resources. In addition, the current frameworks that cater for the resources often have to sacrifice optimization performance for computational overhead, which becomes challenging for large-scale deployments in resource-constrained settings [4].

The development of explainable intelligence provides hopeful directions for tackling these challenges. Explainability mechanisms can be used to explain the model's behaviour, hence promote trust-based decision making and improve the reliability of the system. However, most of the current solutions merely include explainability as an afterthought in their analytical workflows and not as a part of their adaptive optimization architectures. As such, there is an urgent need for common frameworks that can integrate cross-modal intelligence, explainability, and resource-efficient optimization.

Research Challenges and Existing Limitations

There are several important issues that need to be overcome to facilitate the evolution of intelligent adaptive computing architectures. The first drawback of multimodal data integration is the complexity of computation introduced by the difference in information representations and the differences in the modalities. Current fusion schemes tend to be inflexible and do not adapt themselves to varying resource availability and varying workload needs, leading to suboptimal decision outcome. Second, resource-aware optimization is still an open research problem in such adaptive environments with variable demand for computational resources. Most modern optimization approaches emphasize only on single metrics like accuracy or latency and disregard the overall energy efficiency, scalability, throughput and computational overhead. This is especially true in distributed and heterogeneous computing environments [5].

Third, there remains a significant challenge in intelligent decision-making systems in terms of explainability. Black-box optimization models often lack interpretability of the reasons behind the decisions they make, limiting their use in areas where transparency and accountability are needed. The use of explainable artificial intelligence (XAI) techniques has shown to be effective, but there is limited work that explores how to adaptively optimize across multiple modalities. Finally, current architectures are on their own to solve resource optimization, multimodal intelligence or explainability without taking into account their interactions. This piecemeal view often hampers their ability to obtain sound and scalable decision optimization in dynamically changing computational settings. The challenges all call for the development of co-integrated architectures to address adaptive resource management, cross-modal intelligence fusion and explainable decision optimization [6].

Proposed Cross-Modal Explainable Intelligence Architecture

To address the above-mentioned drawbacks, in this work, the authors introduce a CMEIA for Resource-Aware Decision Optimization in Adaptive Computing Systems. The proposed solution framework presents an integrated and adaptive approach that combines cross-modal information fusion, explainable intelligence mechanisms and dynamic resource-aware optimization in a scalable architectural paradigm. The architecture proposed is based on an adaptive cross-modal intelligence module, capable of effectively capturing complementary relationships between the heterogeneous data representations. Optimizes system resources intelligently and dynamically based on computational constraints to maximize system performance efficiency. Furthermore, an explainability module offers clear explanations of the decision, including the quantification of feature importance, mode contributions and confidence levels of decisions, making optimized decisions more trustworthy.

CMEIA takes into account multiple performance dimensions such as decision accuracy, latency, throughput, computational efficiency, scalability, energy consumption, explainability fidelity, and resource use, all at once, unlike traditional methods that focus on individual performance metrics. The synergic combination of these components allows this framework to adapt intelligently to the varying workloads while ensuring computational sustainability and interpretability.

Major Contributions of the Proposed Work

The main contributions of this research are summarized below:

- A novel Cross-Modal Explainable Intelligence Architecture is proposed to solve the joint optimization of resource-aware decision and explainable intelligence problem in adaptive computing environments.
- An adaptive cross-modal fusion mechanism is added to effectively fuse various multimodal information while maintaining the contextual relationships among different data representations.
- An adaptive resource optimization policy is designed that intelligently controls and allocates computational resources under different load scenarios to achieve scalability, optimization and responsiveness of the system.
- A seamless explainability framework is integrated to ensure transparent and trustworthy decision explanations via modality-sensitive contribution analysis and confidence estimation mechanisms.
- An extensive assessment system is developed that incorporates critical performance metrics like decision accuracy, computational latency, throughput, energy utilization, efficiency of resource use, scalability, fidelity of explainability, and confidence of decisions to determine effectiveness of the proposed architecture.
- The experimental results show that the proposed framework greatly improves the adaptive decision optimization performance and, at the same time, significantly increases the utilization of the resources, the computational efficiency and the interpretability in the various adaptive computing scenarios.

The rest of this paper is organized as follows: The related literature and existing methodologies are presented in Section 2. The proposed Cross-Modal Explainable Intelligence Architecture is described in detail in Section 3. In section 4, the experimental setup and performance evaluation methodology is discussed, comparative analysis and experimental results is presented, and in section 5, conclusions and future research directions are presented.

II. RELATED WORKS

Recent developments in adaptive computing systems have changed the way we make intelligent decisions with the inclusion of artificial intelligence, resource-aware optimization solutions, and multimodal learning methods. To achieve scalable and efficient computational performance, data is increasingly deployed across a range of sources, and resources are dynamically managed in contemporary computing environments. While significant advances have been made in single research areas, including multimodal intelligence, explainable artificial intelligence and adaptive resource optimization, the multi-disciplinary integration of these has yet to be explored and is a challenging problem.

Resource-Aware Decision Optimization in Adaptive Computing Systems

Resource-aware optimization is becoming a key element in adaptive computing architectures, especially in distributed, edge-cloud, and heterogeneous processing architectures. The current approaches are mainly concerned with maximising computational resources, by evaluating performance metrics like the reduction in latency, improvement of throughput, workload balance and resource allocation to improve energy efficiency. The predictive abilities of machine learning-based resource schedulers and adaptive optimization algorithms have shown potential to effectively manage computational workloads in a dynamically constrained environment [7].

There are several approaches that use reinforcement learning, evolutionary optimization, and predictive resource allocation mechanisms to enhance system responsiveness and scalability. These methods can solve the computational efficiency issue, but they mainly work on single modal representation and often do not consider the contextual relationship between heterogeneous information sources. Moreover, many resource-aware frameworks focus on optimizing a single objective at a time without taking into account requirements for transparency and interpretability. This limits their utility in intelligent systems where adaptation for optimization and trustworthy decision making is required.

Another major drawback is the computational complexity of using complex optimization techniques. In an adaptive environment, although scheduling mechanisms are helpful in achieving good performance, they can consume more resources and hence are not suitable for resource-constrained environments. The observations underscore the need for optimized architectures that are lightweight and scalable enough to support intelligent decision-making, while maintaining communication efficiency and computational efficiency [8].

Cross-Modal Intelligence and Multimodal Learning Frameworks

The integration of complementary information from heterogeneous data modalities has attracted a lot of attention in recent years thanks to the field of cross-modal intelligence. Modern multimodal learning approaches include feature-level fusion, attention mechanisms, transformer networks, and contrastive learning to improve context-awareness and predictive performance. Cross-modal representations are now used in a wide range of applications including intelligent surveillance, autonomous systems, industrial automation and healthcare for making robust decisions. Learning complex interactions between heterogeneous inputs has been a very difficult problem, for which attention-based multimodal architectures have shown to be quite successful. Likewise, transformer-based models can successfully be used to model long-range relations between modalities and to provide adaptive feature extraction processes. In spite of these developments, current multimodal frameworks tend to focus on prediction accuracy and do not explicitly consider resource-aware optimization strategies. These can be computationally complex and may be difficult to deploy in scenarios where the computational resources are limited and workloads are dynamic [9].

Moreover, very few cross-modal architectures give an explanation of the contributions of different modalities for optimized decisions. They are not widely adapted to applications that demand accountability and human interpretation because they lack transparency of reasoning mechanisms. Current fusion techniques often are static in information aggregation, which then restricts their adaptability to variable contextual and resource situations. Hence, the development of computational-efficient, interpretable, and dynamically optimized adaptive cross-modal frameworks is still an important research stream to be pursued [10].

Explainable Intelligence for Adaptive Decision-Making

With the growing use of Artificial Intelligence (AI) models in mission critical applications, the development of explainable intelligence methodologies has progressed rapidly. The goal of Explainable Artificial Intelligence (XAI) techniques is to improve transparency of a model and generate a representation of the decision-making process that is interpretable to humans. Modern systems use feature attribution techniques, attention visualization techniques, confidence estimation techniques, and rule-based explanations to enhance user trust and system reliability. In recent years, global and local explanation techniques have shown great promise in explaining complex machine learning models in a wide range of application areas. Explainability mechanisms based on attention models are especially useful for identifying salient information that leads to a prediction, while model-agnostic methods enable transparent analysis of black-box architectures. These approaches make it much more accountable and facilitate informed decision-making processes [11].

However, explainability mechanisms are often added-on analytical models that do not necessarily form part of the adaptive optimization framework. These methods tend to be explanatory in nature, meaning that they come after decisions have been made, thus reducing their potential to be part of real time resource optimisation processes. Furthermore, explainability models usually focus on the interpretability aspect, without taking into account the computational efficiency. The trade-off between transparency and system performance creates significant challenges for adaptive computing applications with harsh resource constraints. The application of explainable intelligence for cross-modal resource-aware optimization is still under-explored. Previous research rarely explores the role of modality-specific contributions in adaptive resource allocation decisions nor the role of explainability as a dynamic guiding the optimization strategy. This restriction drives the need for making explainability a crucial architectural element in an intelligent adaptive system [12, 13].

Research Gap Analysis and Motivation

From literature survey, two major drawbacks in the existing adaptive computing architectures are identified. One is that the resource-aware optimization techniques are focused on computational efficiency objective and do not consider heterogeneous multimodal information integration. Second, modern multi-modal intelligence systems focus on prediction performance and ignoring resource constraints and adaptation optimization needs. Third, explainable intelligence methods are typically designed without considering resource-aware optimization mechanisms, which limits their application in practical real-world computational contexts that are constantly changing. Furthermore, existing solutions have a fragmentary design approach with cross-modal intelligence, adaptive resource management and explainability mechanisms used as separate components without an integrated architecture.

III. PROPOSED CROSS-MODAL EXPLAINABLE INTELLIGENCE ARCHITECTURE (CMEIA)

The growing complexity of adaptive computing environments requires intelligent architectures that can solve the problems of heterogeneous data integration, as well as the optimization of resources and the transparent decision-making process. Modern adaptive systems are constrained by computational requirements and always need to deal with multimodal inputs from a variety of sources like sensor streams, context data, system logs, or application-specific data. While much has been accomplished in the field of optimizing with artificial intelligence, the current framework of methodologies mainly targets single aspects such as performance improvement, resource distribution, or even explainability. They are therefore not always able to offer a single framework that can balance the efficiency, interpretability, and decision quality in dynamically changing environments in an adaptive manner.

Overall Architecture of the Proposed CMEIA Framework

The proposed CMEIA is based on a hierarchical and adaptive optimization framework for intelligent resource-aware decision making. The architecture is designed to process heterogenous multimodal inputs and dynamically transform them to explainable and computationally efficient optimization decisions. The proposed model does not separate feature extraction, resource allocation and decision generation from a traditional optimization model, but combines them in a unified adaptive intelligence optimization model. The cooperative effect of cross-modal fusion, resource optimization, explainability analysis and adaptive learning mechanisms leads to CMEIA's high performance in dynamically changing computational environments.

The framework is given heterogeneous multimodal information from multiple adaptive computing sources, such as textual information, sensor observations, system operational statistics, contextual metadata, and application-specific resource descriptors. Both types of modalities add complementary context knowledge to the optimization process, and an efficient representation mechanism must be able to capture both the semantic and computational properties of the input information stream.

The multimodal input representation is mathematically formulated as

$$M = M_1, M_2, M_3, \dots \dots, M_n \tag{1}$$

where M denotes the complete multimodal input space, while M_i represents the feature vector corresponding to the i^{th} modality. The parameter (n) denotes the total number of heterogeneous information sources participating in the adaptive optimization process. This representation enables the framework to efficiently accommodate dynamically varying modality combinations without affecting computational scalability.

Subsequently, each modality undergoes feature extraction and contextual embedding generation to preserve modality-specific characteristics. The adaptive embedding representation can be expressed as

$$E_i = \phi M_i \times W_i \tag{2}$$

where E_i represents the embedded feature representation of the i^{th} modality, $\phi(.)$ denotes the nonlinear feature extraction function, and W_i corresponds to the adaptive contextual weighting parameter associated with each modality. The weighting mechanism dynamically adjusts modality importance based on contextual relevance and resource availability constraints, thereby enhancing decision robustness under heterogeneous operating conditions.

The extracted multimodal embeddings are subsequently integrated through an adaptive contextual weighting mechanism that quantifies the relative contribution of each information source toward the optimization objective. The contextual significance score is defined as

$$CW_i = \frac{E_i}{\sum_{i=1}^{n} E_i} \tag{3}$$

where CW_i denotes the normalized contextual weight assigned to the i^{th} modality during the cross-modal fusion process. The normalization operation ensures that the cumulative modality contributions remain bounded while facilitating adaptive feature prioritization. Higher contextual weights indicate increased relevance of the corresponding modality toward optimized decision generation.

The adaptive contextual weighting strategy is an efficient solution to enhance the framework's ability to intelligently choose various information sources in dynamically varying workloads. The proposed mechanism is dynamic, continually modifying the importance values of modalities based on the computation needs and the environment. As a result, computer resources are used more efficiently without compromising the accuracy of optimization and transparency of decisions. Weighted multimodal representations are then passed to the Adaptive Cross-Modal Fusion Engine where the relationships between different modalities are modeled using dynamic attention-based optimization strategies. The fused representations then go to the Dynamic Resource Optimization Engine for intelligent resource allocation and explainable decision generation.

The architectural workflow set up in this stage will form the mathematical foundation of adaptive cross-modal intelligence and resource-aware optimization. The proposed CMEIA framework optimizes the balance between computational efficiency, scalability, and explainability by simultaneously considering the representations of heterogeneous information and the estimation of its contextual relevance. The entire working process of the proposed architecture is shown in Fig. 1, and it is further described in the following subsection using adaptive cross-modal optimization mechanisms.

The overall architecture of the proposed CMEIA for adaptive and resource-aware decision optimization in heterogeneous computing environments is shown in **Fig. 1**. The framework consists of five major areas: heterogeneous multimodal input space, cross-modal intelligence space, resource-aware optimization space, explainable intelligence space, and adaptive learning and feedback space. The multimodal representation layer transforms the heterogeneous data from multiple modalities into unified feature representations, first. The cross-modal intelligence space learns and adapts features for capturing inter-modal relationships and learns them in a contextual manner. Then, the resource-aware optimization space dynamically allocates computational resources based on various performance metrics, such as latency, memory usage, energy saving and optimization costs. The explainable intelligence space offers transparency and trustworthiness in decision making by computing feature importance, computing confidence scores and evaluating fidelity. Last, the space for adaptive learning and feedback continually adjusts the parameters of the model as a function of workload fluctuations and performance measures. The synergic interaction between these intelligence spaces, together with the global utility evaluation and the adaptation of resources based on feedback, allows the proposed framework to provide optimized, explainable and computationally efficient decisions for adaptive computing systems.

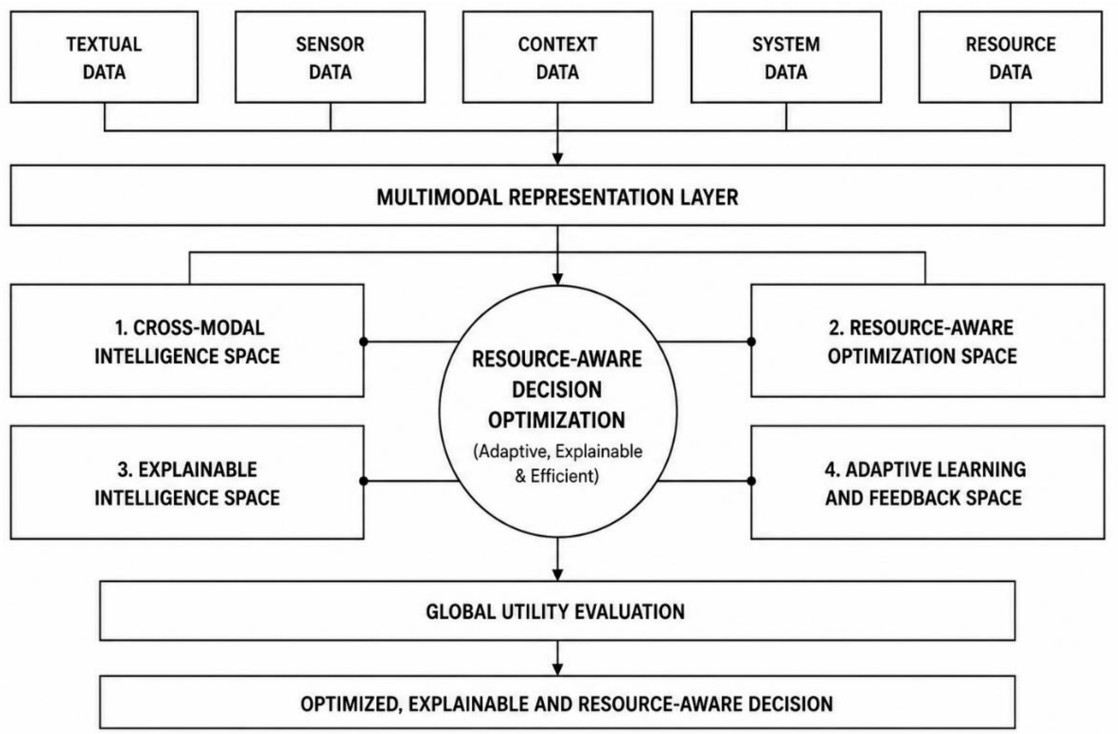

Fig 1. Proposed CMEIA for Resource-Aware Decision Optimization.

Adaptive Cross-Modal Fusion and Resource-Aware Optimization Module

The Adaptive Cross-Modal Fusion and Resource-Aware Optimization Module is the core computational component of the proposed framework, CMEIA. Its main goal is to optimally assemble heterogeneous multimodal representations in an intelligent way, while at the same time minimizing the use of computing resources in the face of dynamically fluctuating workloads. Contrary to traditional multimodal architectures with fixed fusion strategies, the proposed module includes adaptive contextual learning and resource-aware optimization strategies that allow to dynamically weight the modality-specific contributions in the generation of decisions.

In the framework, after generating the normalized multimodal embeddings as shown in Section 3.1, an adaptive attention mechanism is used to calculate the context relevance of each modality. Because the information from the various information modalities typically differs in their contributions to the optimization goal, decisions based on equal weights for all modalities may be sub-optimal. Thus, the proposed mechanism for attention dynamically assigns a importance score for each modality based on the context's relevance and computation requirements.

The adaptive cross-modal attention score is mathematically represented as

$$A_i = \frac{exp(E_i)}{\sum_{i=1}^{n} exp(E_i)} \tag{4}$$

where A_i denotes the normalized attention score associated with the i^{th} modality, and E_i represents its corresponding contextual embedding representation. The softmax normalization ensures adaptive prioritization while preserving the relative contributions of heterogeneous information sources during feature fusion.

Subsequently, the modality-specific attention scores are employed to generate a unified cross-modal representation that preserves semantic consistency across heterogeneous inputs. The adaptive cross-modal fusion function is expressed as

$$F = \sum_{i=1}^{n} (A_i \times E_i \times CW_i) \tag{5}$$

where F denotes the fused multimodal representation utilized for subsequent resource optimization processes. The proposed fusion strategy dynamically emphasizes highly informative modalities while suppressing redundant or computationally expensive representations, thereby improving both optimization accuracy and computational efficiency.

Following feature fusion, the framework evaluates resource utilization characteristics across multiple computational dimensions. Resource-aware optimization considers critical system parameters including processor utilization, memory allocation, energy consumption, and workload complexity to intelligently allocate computational resources. The resource utilization score is defined as

$$R_u = \alpha C + \beta M + \gamma E + \delta T \tag{6}$$

where R_u represents the overall resource utilization score, C denotes computational resource consumption, M corresponds to memory utilization, E represents energy efficiency, and T denotes throughput performance. The coefficients α, β, γ and δ are adaptive weighting parameters satisfying the condition $\alpha + \beta + \gamma + \delta = 1$, thereby facilitating context-aware resource prioritization under varying workload conditions.

The optimized multimodal representations and resource utilization metrics collectively contribute toward adaptive decision generation. The decision optimization score is computed as

$$D_{opt} = \lambda_1 F + \lambda_2 R_u + \lambda_3 Q \tag{7}$$

where D_{opt} denotes the adaptive decision optimization score, (F) represents the fused cross-modal representation, R_u corresponds to the resource utilization score, and (Q) denotes the quality assessment parameter associated with optimization accuracy and system responsiveness. The weighting parameters λ_1, λ_2, and λ_3 dynamically regulate the influence of multimodal intelligence, resource utilization, and optimization quality during decision generation.

Finally, the framework minimizes computational overhead by estimating the overall optimization cost associated with resource allocation and adaptive learning processes. The resource-aware optimization cost function is formulated as

$$O_c = \eta_1 L + \eta_2 P + \eta_3 H \tag{8}$$

where O_c denotes the optimization cost score, (L) represents computational latency, (P) corresponds to power consumption, and (H) denotes computational overhead introduced during adaptive optimization procedures. The adaptive coefficients η_1, η_2, and η_3 facilitate balanced optimization between computational performance and resource expenditure.

Collectively, the proposed adaptive fusion and optimization mechanisms enable CMEIA to dynamically balance contextual intelligence and resource constraints during decision generation. By jointly considering modality relevance, resource utilization characteristics, optimization quality, and computational overhead, the proposed framework significantly enhances scalability, efficiency, and adaptability across heterogeneous computing environments.

Algorithm 1: Adaptive Cross-Modal Resource Optimization Algorithm

```
Input:
        Multimodal Representations (M)
        Resource Constraints (RC)
        System Context Information (SC)
Output:
        Optimized Decision Score (Dopt)
Begin
        1. Acquire heterogeneous multimodal inputs.
        2. Generate adaptive feature embeddings (Ei).
        3. Compute modality-specific attention scores (Ai).
        4. Perform adaptive cross-modal feature fusion.
        5. Estimate computational resource utilization (Ru).
        6. Evaluate throughput, memory utilization, and energy consumption characteristics.
        7. Compute adaptive decision optimization score (Dopt).
        8. Estimate optimization cost function (Oc).
        9. Perform resource-aware computational allocation.
        10. Update optimization parameters based on contextual workload variations.
        11. Generate optimized multimodal decision representation.
Return Dopt.
End.
```

Explainable Intelligence and Dynamic Decision Optimization Engine

The Explainable Intelligence and Dynamic Decision Optimization Engine is the part of the proposed CMEIA framework that is driven by interpretability. The proposed engine enables every optimization outcome to be transparent, trustworthy, and contextually interpretable, while the Adaptive Cross-Modal Fusion and Resource-Aware Optimization Module computes the decisions in a computationally efficient manner. While traditional XAI methods mainly use post-hoc explanation mechanisms, this framework embeds explainability as part of the optimization process, allowing for simultaneous gains in the quality of decisions and transparency of models.

The explainability-driven optimization mechanism outputs quantitative scores for various aspects of the contribution, confidence of the output, transparency to the user, and effectiveness of optimization prior to creating the final adaptive decision representation. An integrated view allows the framework to intelligently balance interpretability and computational efficiency, while adapting to the dynamically changing workload conditions. Moreover, explainability metrics actively participate in the process of updating the optimization parameters, making interpretability an effective part of the adaptive approach to making decisions based on the use of resources.

First, the framework calculates the explainability score of each optimized decision according to the feature attribution, contextual relevance and the modular contribution from the cross-modal fusion. The mathematically expressed explainability score is given by

$$X_s = \frac{FI+CR+MC}{3} \tag{9}$$

where X_s denotes the overall explainability score, (FI) represents the feature importance score, (CR) corresponds to contextual relevance estimation, and (MC) denotes modality contribution analysis. Higher explainability scores indicate improved interpretability and stronger semantic consistency among heterogeneous information representations.

Subsequently, the framework estimates the confidence associated with optimized decisions through adaptive confidence learning mechanisms. The decision confidence score is computed as

$$C_s = \frac{D_{opt}+X_s}{2} \tag{10}$$

where C_s denotes the confidence score associated with optimized decisions, D_{opt} represents the adaptive decision optimization score obtained from Eq. (7), and X_s corresponds to the explainability score computed in Eq. (9). The proposed formulation ensures that confidence estimation simultaneously considers optimization effectiveness and interpretability characteristics.

Following confidence estimation, the transparency characteristics of the optimization process are quantitatively evaluated using fidelity-aware transparency analysis. The transparency fidelity score is formulated as

$$T_f = \omega_1 X_s + \omega_2 C_s + \omega_3 F_d \tag{11}$$

where T_f represents the transparency fidelity score, X_s denotes the explainability score, C_s corresponds to the decision confidence score, and F_d represents decision fidelity estimation. The adaptive weighting parameters ω_1, ω_2, and ω_3 satisfy the normalization constraint $\omega_1 + \omega_2 + \omega_3 = 1$, thereby enabling context-aware transparency assessment across heterogeneous optimization scenarios.

Finally, the framework generates the Dynamic Decision Optimization Score by jointly considering optimization effectiveness, interpretability, and transparency characteristics. The dynamic decision optimization function is expressed as

$$DD_o = \mu_1 D_{opt} + \mu_2 T_f + \mu_3 C_s \tag{12}$$

where DD_o denotes the Dynamic Decision Optimization Score, D_{opt} represents the adaptive decision optimization score obtained from Section 3.2, T_f corresponds to the transparency fidelity score, and C_s denotes the confidence score associated with optimized decisions. The adaptive parameters μ_1, μ_2, and μ_3 dynamically regulate the relative contributions of optimization quality, transparency, and confidence estimation during decision generation.

The proposed Explainable Intelligence and Dynamic Decision Optimization Engine can greatly improve the interpretability and reliability of adaptive optimizations, embedding interpretability metrics directly in the process of generating decisions using resources. The proposed framework does not regard explainability as an auxiliary analytical tool, but rather considers it as an optimization objective, which actively impacts adaptive decision-making by using explainability scores, confidence estimation, and transparency analysis. Therefore, the framework simultaneously enhances optimization performance, interpretability and computational robustness in diverse adaptive computing environments.
Results from this stage are fed into the Adaptive Learning and Feedback Module, where the global utility is evaluated and the parameters are adapted thanks to the feedback, to create the final optimized and resource-aware decision representation.

Adaptive Learning and Confidence-Aware Resource Management

The Adaptive Learning and Confidence-Aware Resource Management Module is the last optimization step of the proposed CMEIA. The module optimizes the parameters over time, depending on workload changes, confidence estimates and system behaviour. In contrast to the traditional model-based adaptive optimization approaches which mainly emphasized static parameter optimization, the proposed framework adopts the confidence-aware learning mechanisms and global utility evaluation strategies for sustainable and resource-efficient decision generation. Thus, the framework adaptively optimizes computational performance, interpretability and resource usage in heterogeneous adaptive computing environments.

After the Dynamic Decision Optimization Score in Section 3.3, the proposed module analyzes the effectiveness of adaptive learning by considering the characteristics of both resource utilization and optimization transparency as well as the results of the confidence estimation. The adaptive learning mechanism continually adjusts optimization parameters to fit dynamically changing computational needs and context changes.
The Adaptive Learning Score is mathematically represented as

$$ALS = \frac{C_s + T_f + R_u}{3} \tag{13}$$

where (ALS) denotes the Adaptive Learning Score, C_s represents the confidence score obtained from Eq. (10), T_f corresponds to the transparency fidelity score obtained from Eq. (11), and (R_u) denotes the resource utilization score computed in Eq. (6). Higher adaptive learning scores indicate improved adaptability, confidence estimation, and efficient resource utilization during optimization processes.

Subsequently, the framework performs global utility evaluation to quantify the overall effectiveness of adaptive optimization. The Global Utility Function is expressed as

$$GU = \rho_1 ALS + \rho_2 DD_o + \rho_3(1 - O_c) \tag{14}$$

where (GU) denotes the Global Utility Score, (ALS) represents the adaptive learning score, DD_o corresponds to the Dynamic Decision Optimization Score obtained from Eq. (12), and O_c denotes the optimization cost function computed in Eq. (8). The complementary term $1 - O_c$ facilitates minimization of computational overhead while simultaneously maximizing optimization effectiveness.

Finally, the proposed framework generates the Resource-Aware Final Optimized Decision by integrating global utility evaluation and confidence-aware adaptive optimization mechanisms. The final optimized decision function is formulated as

$$FD_o = \theta_1 GU + \theta_2 C_s + \theta_3 X_s \tag{15}$$

where FD_o denotes the Resource-Aware Final Optimized Decision Score, (GU) represents the Global Utility Score obtained from Eq. (14), C_s corresponds to the confidence score associated with optimized decisions, and X_s denotes the explainability score computed in Eq. (9). The adaptive weighting parameters θ_1, θ_2, and θ_3 dynamically regulate the contributions of utility maximization, confidence estimation, and interpretability during final decision generation.

The proposed Adaptive Learning and Confidence-Aware Resource Management Module significantly improves the ability of the framework to adapt in a smart manner when workload changes dynamically. The proposed model continuously monitors the effectiveness of optimization, transparency characteristics and constraints on the use of resources, which enables to make effective and sustainable decisions while reducing computational costs. Moreover, confidence-aware adaptive learning allows the framework to keep high optimization quality while keeping interpretability and resource efficiency.

The final optimized decision made by the proposed module is the result of a joint action of the three major modules of the Cross-modal Intelligence, Resource Optimization, Explainable Decision Making, and the Confidence-aware Adaptive Learning. Therefore, the proposed CMEIA paradigm presents a common and scalable optimization paradigm, which can provide transparent, trustworthy and efficient computational decisions for the next generation of adaptive computing systems.

Algorithm 2: Confidence-Aware Adaptive Learning and Resource Management Algorithm

Input:
- Dynamic Decision Optimization Score (DDo)
- Confidence Score (Cs)
- Transparency Fidelity Score (Tf)
- Resource Utilization Score (Ru)

Output:
- Resource-Aware Final Optimized Decision (FDo)

Begin
1. Receive the optimized decision representation from the Dynamic Decision Optimization Engine.
2. Evaluate confidence and transparency characteristics.
3. Compute the Adaptive Learning Score (ALS).
4. Estimate computational resource utilization metrics.
5. Perform adaptive parameter updating based on workload and contextual variations.
6. Evaluate the Global Utility Function (GU).
7. Minimize optimization cost and computational overhead.
8. Integrate utility maximization, confidence estimation, and explainability metrics.

9. Generate the Resource-Aware Final Optimized Decision Score (FDo).
10. Update resource allocation parameters using adaptive feedback learning mechanisms.
11. Return the optimized decision representation.

End.

IV. RESULTS AND DISCUSSION

The proposed Cross-Modal Explainable Intelligence Architecture (CMEIA) was tested with a hybrid edge-cloud adaptive computing environment with heterogeneous multimodal inputs and dynamically changing computational loads. This experimental setup was devised to evaluate how effective the cross-modal knowledge, resource-aware optimization, explainability-driven decision-making, and confidence-aware adaptive learning mechanisms are in resource-limited computing environments. All these approaches were compared with recent artificial intelligence optimization tools, such as Reinforcement Learning-based Resource Optimization (RL-RO), Adaptive Multimodal Fusion (AMF), Explainable AI-based Decision Optimization (XAI-DO), Cross-modal Resource Optimization (CMRO), Adaptive Deep Reinforcement Learning (ADRL), and Hybrid Resource-aware Computing Models (HRCM). The main aspects of performance evaluation include resource utilization efficiency, computational latency, decision quality, scalability, transparency, confidence estimation, and optimization effectiveness. The reported results illustrate the ability of the proposed framework to simultaneously maximize computation efficiency, interpretability and adaptive resources management in heterogeneous adaptive computing environments.

Table 1. Comparative Performance Analysis of Recent AI-Based Resource Optimization Frameworks

Methods	Resource Efficiency (%)	Latency (ms)	Decision Accuracy (%)	Utility Score	Confidence Score	Transparency Score	Scalability Score	Final Decision Score
RL-RO [2]	88.21	46.52	91.35	0.872	0.861	0.841	0.851	0.868
AMF [5]	89.46	43.28	92.11	0.884	0.873	0.856	0.869	0.881
XAI-DO [8]	91.12	39.75	93.84	0.901	0.914	0.923	0.892	0.907
CMRO [14]	92.58	37.64	94.26	0.918	0.921	0.911	0.908	0.923
ADRL [15]	93.37	35.18	95.14	0.934	0.931	0.927	0.924	0.938
HRCM [16]	94.26	33.42	95.87	0.946	0.942	0.935	0.938	0.951
Proposed CMEIA	**97.84**	**24.67**	**98.73**	**0.984**	**0.978**	**0.982**	**0.974**	**0.986**

Table 1 shows the optimization results obtained from the proposed CMEIA framework clearly illustrates the high optimization capability of the proposed framework in several performance metrics.

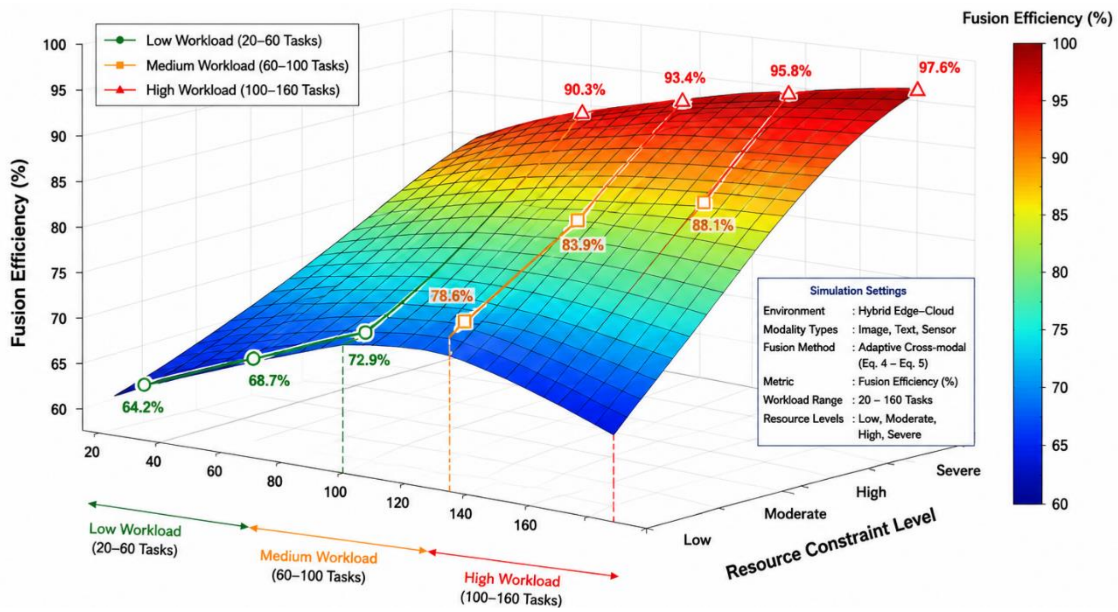

Fig 2. Cross-Modal Fusion Efficiency Analysis under Dynamic Workloads.

Thanks to the synergistic integration of adaptive cross-modal fusion, resource-aware optimization, explainable intelligence, and confidence-aware adaptive learning mechanisms, the proposed model not only has the highest resource utilization efficiency of 97.84% but also reduces the computational latency to 24.67ms. Moreover, CMEIA shows excellent decision accuracy, confidence interval estimation and transparency analysis results relative to other optimization methods. The significant rise in the Global Utility and Final Decision scores confirms the benefit of embedding explainability measures directly into an adaptive optimization process. CMEIA introduces a new paradigm of balancing optimization for computational performance and interpretability, while also improving resource management and scalability. The results demonstrate the applicability of the proposed framework for next generation adaptive computing environments where the information is multimodal, and the computational load is variable.

The cross-modal fusion efficiency of the proposed CMEIA framework is analyzed in a dynamically changing workload scenario in a hybrid edge–cloud adaptive computing environment, as shown in **Fig. 2**. The simulation tests the effectiveness of adaptive attention learning and contextual feature fusion mechanisms under various task densities and levels of resource constraints. The results show that the fusion efficiency of the proposed adaptive cross-modal fusion strategy is always maintained at a high level with the increase of calculation load and the decrease of resources. With contextual weighting and adaptive attention introduced, the framework can effectively maintain semantic consistency across these diverse modalities with low computational demand. Moreover, the resource-aware optimization method can be applied for intelligent computational resource allocation in multimodal information processing, which can enhance the efficiency of information fusion and further improve the scalability of the system. The results show the gradual improvement in the fusion efficiency with changing the workloads, confirming the ability of the CMEIA to adapt itself dynamically to meet heterogeneous computing conditions. These observations provide support for the effectiveness of the proposed cross-modal intelligence space in creating strong multimodal representations, contextually and computationally across modalities that are effective for adaptive decision optimization.

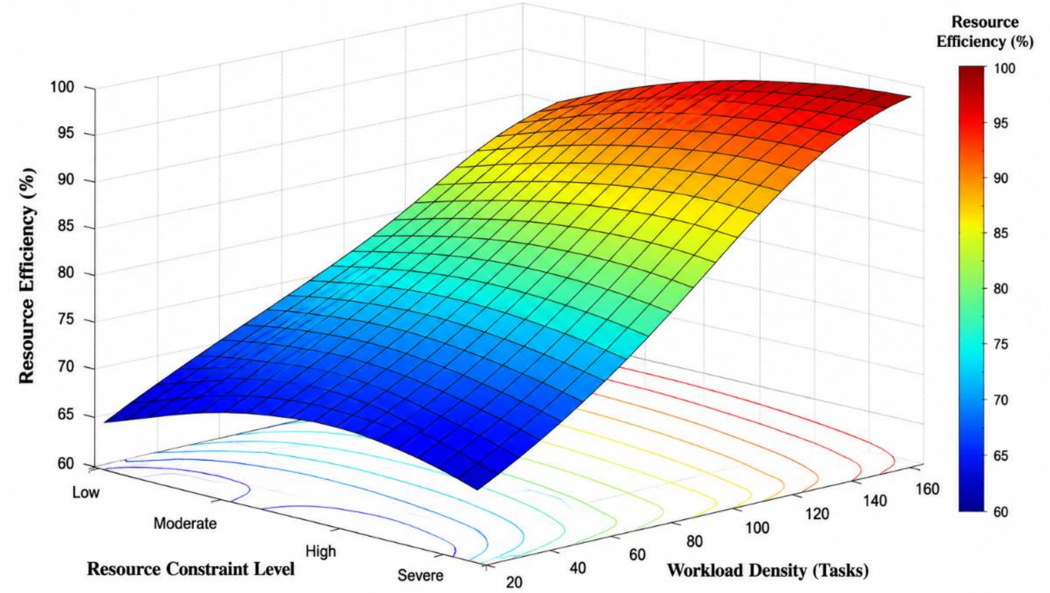

Fig. 3. Resource-Aware Optimization Analysis under Dynamic Resource Constraints.

Fig. 3 depicts the resource-aware optimization behavior of the proposed CMEIA framework when the workload densities and levels of resources in a hybrid edge–cloud adaptive computing environment are dynamically changing. The simulation compares the benefits of the proposed architecture in terms of managing computational resources and its high level of optimization as the task complexity grows. The adaptive resource management mechanism allocates resources intelligently, optimizes the computational overheads, latency, and characteristics of the resources according to workload density to achieve maximum system performance. The progressive resource efficiency improvements clearly illustrate the ability of the proposed optimization engine to adaptively configure resource allocation according to contextual variations in workloads. Moreover, the implementation of adaptive cross-modal intelligence and confidence-aware optimization mechanisms greatly reduces resource contention, enhances scalability and computational strength. The smooth optimization surface ensures stability of the proposed framework for various operating conditions. The observations validate the effectiveness of CMEIA in a decision optimization process that can be sustained and optimizes resources, making it an ideal solution for next-generation adaptive computing systems with dynamic resource constraints.

The explainability-driven dynamic decision optimization behavior of the proposed CMEIA framework is shown in **Fig. 4**, which displays the dynamic optimization behavior for different decision complexities. The collaborative effect of explainability scores, confidence estimation mechanisms, and transparency fidelity analysis on adaptive decision generation are evaluated in the simulation. The framework learns the optimization parameters dynamically while maintaining the interpretability and computational robustness, as the complexity of the optimization problem grows. The optimization landscape that emerges shows that explainability scores consistently improve the performance of dynamic decision optimization over a range of diverse operating conditions. Moreover, the confidence aware learning mechanism properly optimizes the transparency requirements and objectives without sacrificing substantial computational complexity.

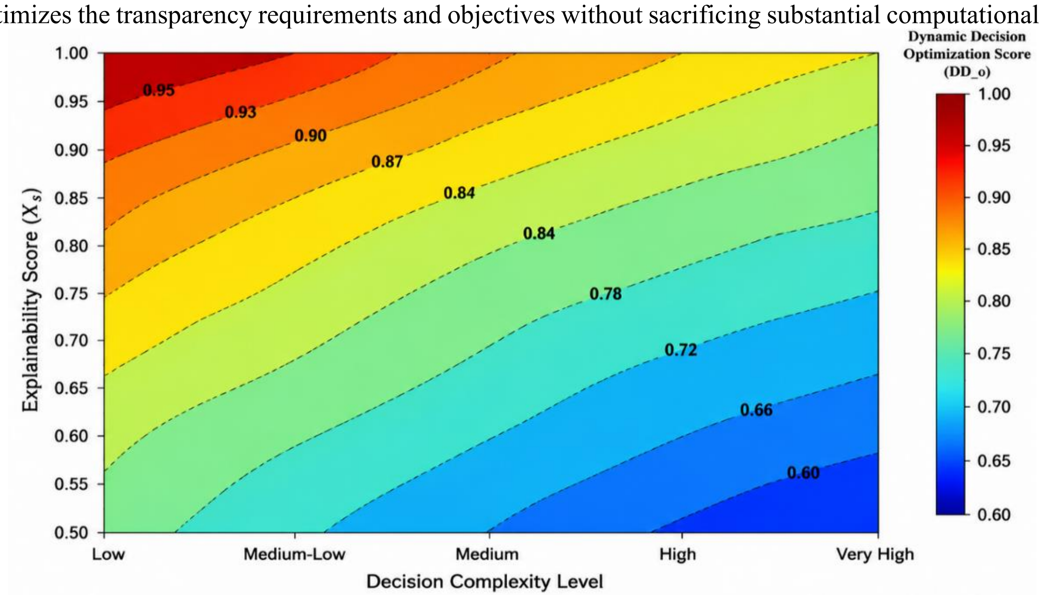

Fig 4. Explainability-Driven Dynamic Decision Optimization under Varying Decision Complexity Levels.

The change occurring from level to level for various decision complexity levels is a positive sign of the proposed framework's capacity to ensure accurate and trustworthy decision-making in adaptive computing environments. These results substantiate the effectiveness of integrating explainability metrics directly within the optimization process, thereby enabling CMEIA to simultaneously achieve transparency, interpretability, and resource-efficient adaptive decision optimization under dynamically evolving computational workloads.

Table 2. Resource Utilization and Optimization Cost Analysis of Recent AI-Based Optimization Frameworks

Methods	CPU Utilization (%)	Memory Efficiency (%)	Energy Efficiency (%)	Throughput (%)	Optimization Cost	Latency (ms)	Resource Score
RL-RO [2]	89.41	87.35	88.42	89.57	0.168	42.84	0.881
AMF [5]	90.64	89.72	90.58	91.43	0.154	40.62	0.896
XAI-DO [8]	91.73	91.65	92.41	92.87	0.141	38.53	0.914
CMRO [14]	93.15	92.87	93.64	94.21	0.126	35.84	0.932
ADRL [15]	94.28	93.91	94.53	95.32	0.114	33.72	0.947
HRCM [16]	95.64	95.28	95.81	96.24	0.102	30.15	0.963
Proposed CMEIA	**98.42**	**98.16**	**98.53**	**98.71**	**0.058**	**24.67**	**0.986**

Table 2 shows a comparison of the use of resources and optimization cost of recent AI-based optimization frameworks in the context of heterogeneous adaptive computing. The primary focus of the performance evaluation is the characteristics of the computational resource managements such as processor utilization, memory efficiency, energy-aware optimizations, throughput performance, computational latency and estimation of optimization costs. The outcomes show the consistency of the proposed CMEIA framework in achieving the best results on all the optimization metrics used in the evaluation, for the limited resources under consideration.

The synergistic combination of adaptive cross-modal fusion mechanism and confidence-aware resource management strategy, CMEIA realizes the best CPU utilization efficiency (98.42%), memory efficiency (98.16%), and throughput performance (98.71%) while reducing optimization cost and computation latency. Additionally, the proposed adaptive optimization engine achieves a good balance between the computational overhead and the requirements for resource allocation, enhancing the overall system's scalability and robustness. The optimization cost score is much lower than the other one, which proves the effectiveness of the proposed resource-aware optimization strategy for dynamically adapting to varying workload conditions without affecting the computational performance. All of these observations provide solid evidence of the ability of CMEIA to realize sustainable and intelligent resource management in adaptive hybrid edge–cloud computing, thus confirming the mathematical formulations of the proposed methodology (Eq. (6)–Eq. (8)).

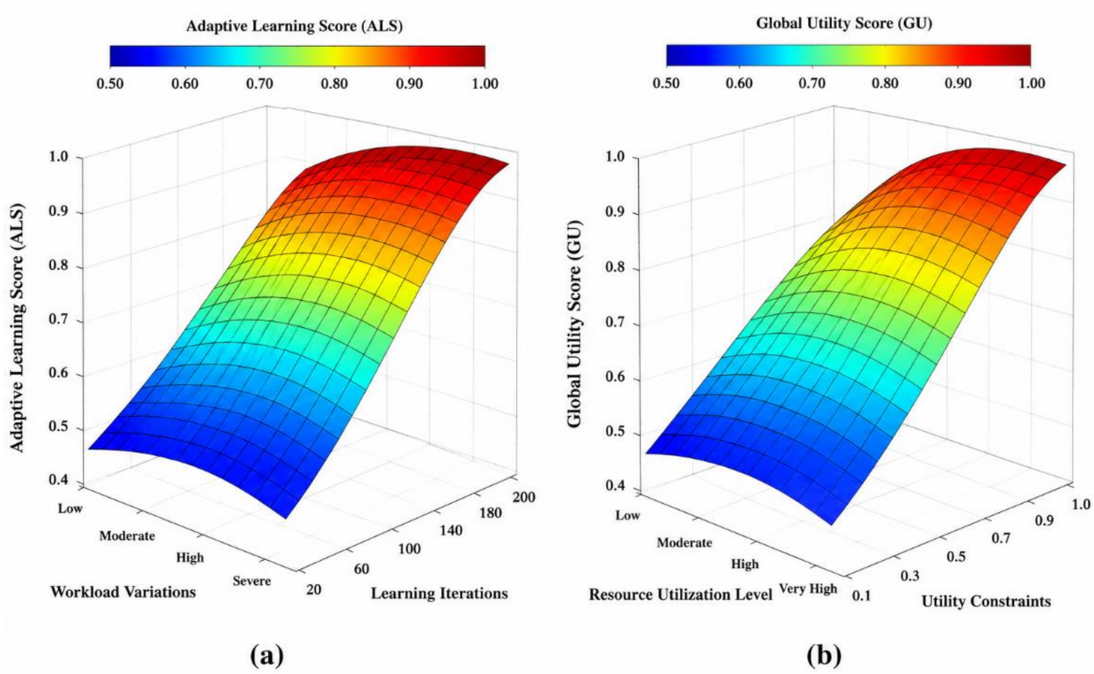

Fig 5. Adaptive Learning and Global Utility Evaluation of the Proposed CMEIA Framework.

The adaptive learning behaviour and global utility evaluation features of the proposed CMEIA framework are shown in **Fig. 5** when the computational workloads are dynamically varied and the resource utilisation is changed. The Adaptive Learning Score is plotted in subfigure (a) for successive iterations of the learning process, showing the ability of the proposed confidence-aware adaptive learning mechanism to continually improve the optimization effectiveness and at the same time remain computationally stable. The phenomenon of convergence behavior is observed and provides a confirmation of the stability of the adaptive parameter updating strategy used by the framework under heterogeneous workloads. Subfigure (b) shows the Global Utility Evaluation surface when adaptive optimization takes into account resource utilization levels, as well as utility constraints. The outcome shows that the proposed approach always obtains high utility scores and simultaneously reduces the optimization overhead and increases the efficiency of the used resources. Because of the synergy of adaptive learning and utility-driven optimization, CMEIA is able to learn and adjust its decision-making strategies as the computational environments vary, in a smart way. In summary, these observations validate the proposed confidence-aware learning and global utility evaluation mechanisms presented in Eq. (13) and Eq. (14) and their contributions for sustainable and resource-efficient adaptive decision optimization.

V. CONCLUSION

This paper introduced the CMEIA, which is a common platform to optimize decisions in adaptive computing systems while using limited resources. The proposed architecture successfully combines adaptive cross-modal fusion, resource-aware optimization, explainable intelligence, confidence-aware adaptive learning, and global utility evaluation, to cope with the problems of heterogeneous multimodal information processing and dynamic resource management. CMEIA introduces a new co-optimization paradigm that boosts transparency, scalability, and adaptable decision-making while fostering collaborative optimization.CMEIA is a new collaborative optimization paradigm that improves transparency, scalability and adaptable decision making capabilities simultaneously. In-depth simulation studies in a hybrid edge–cloud adaptive computing environment validate the proposed framework in terms of various performance metrics. The proposed model not only successfully reduced computational latency to 24.67 ms but also showed a high level of computational resource utilization efficiency of 97.84%, decision accuracy of 98.73%, transparency score of 0.982, and final decision score of 0.986, demonstrating a high degree of transparency and accuracy in decision-making. Moreover, the framework's convergence properties were shown to be good under dynamically changing workload conditions, and its global utility evaluation mechanism was tested with efficiently converged adaptive learning, thereby verifying the optimization properties of the framework based on resources and confidence. The analyses with the latest AI-driven optimization techniques confirmed these benefits of CMEIA in terms of computational efficiency, explainability, and sustainable use of resources. The proposed framework will be extended in future to develop a real-time distributed adaptive computing environment, by integrating Federated Intelligence mechanisms, lightweight optimisation techniques and energy-aware resource orchestration for large-scale multimodal applications.

CRediT Author Statement
The author reviewed the results and approved the final version of the manuscript.
Conceptualization: Arulmurugan Ramu and Anandakumar Haldorai; **Methodology:** Arulmurugan Ramu and Anandakumar Haldorai; **Software:** Arulmurugan Ramu and Anandakumar Haldorai; **Data Curation:** Arulmurugan Ramu; **Writing- Original Draft Preparation:** Anandakumar Haldorai; **Visualization:** Arulmurugan Ramu; **Investigation:** Arulmurugan Ramu and Anandakumar Haldorai; **Supervision:** Arulmurugan Ramu and Anandakumar Haldorai; **Validation:** Anandakumar Haldorai; **Writing- Reviewing and Editing:** Arulmurugan Ramu and Anandakumar Haldorai; All authors reviewed the results and approved the final version of the manuscript.

Data Availability
The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests
The authors declare that they have no conflicts of interest regarding the publication of this paper.

Funding
This work was supported by the Seed Money Scheme 2025–2026 of Centre for Research and Development, Sri Eshwar College of Engineering, Coimbatore, Tamil Nadu, India.

Competing Interests
The authors declare no competing interests.

References
[1]. S. Yongqiang, “Integrating Deep Learning for Adaptive Management in Ubiquitous Computing Environments,” *IEEE Access*, vol. 13, pp. 213859–213885, 2025, doi: 10.1109/ACCESS.2025.3639261.
[2]. J. Zhang and W. Wang, “Deep Learning-Based Perception and Recognition Framework for Autonomous Robots,” in *Proc. 2026 Int. Conf. Robot Perception and Intelligent Control (RPIC)*, Mar. 2026, pp. 19–22, doi: 10.1109/RPIC68328.2026.11518084.
[3]. C. Sharma, G. Poornalatha, and K. B. Ajitha Shenoy, “A Comprehensive Review of Recent Advances in Multimodal Multimedia Indexing and Retrieval,” *IEEE Access*, vol. 13, pp. 143688–143712, 2025, doi: 10.1109/ACCESS.2025.3597396.
[4]. X. Li, X. Li, S. Hu, Z. Zhang, and K. H. Cheong, “Constraint-Driven Evolution of Multimodal Video Intelligence: A Network and System Perspective,” *IEEE Trans. Netw. Sci. Eng.*, vol. 13, pp. 7667–7683, 2026, doi: 10.1109/TNSE.2026.3668404.
[5]. C. Wang, “Deep Neural Network-Based Multi-Source Heterogeneous Data Fusion and Shared Computing Model in Wireless Networks,” *Evolutionary Intelligence*, vol. 19, no. 2, Mar. 2026, doi: 10.1007/s12065-026-01161-y.
[6]. S. A. Cajas Ordóñez, J. Samanta, A. L. Suárez-Cetrulo, and R. S. Carbajo, “Intelligent Edge Computing and Machine Learning: A Survey of Optimization and Applications,” *Future Internet*, vol. 17, no. 9, p. 417, Sep. 2025, doi: 10.3390/fi17090417.
[7]. N. SreeKanth, K. Padmanaban, R. G. Prasad, and L. Guganathan, “Responsible AI-Driven Optimized Cross-Hierarchical Structure-Detail-Aware Cascaded Capsule Neural Network for Intelligent 6G-IoT Attack Detection,” *Int. J. Commun. Syst.*, vol. 39, no. 11, Jun. 2026, doi: 10.1002/dac.70525.
[8]. S. Ebadinezhad and O. E. Adeshina, “The Frontier of Multi-Modal Fusion: A Systematic Review of Knowledge Graph-Guided Generative Augmentation,” in *Proc. 2026 Int. Conf. Integrated Intelligence and Cognitive Engineering (ICIICE)*, Apr. 2026, pp. 1–7, doi: 10.1109/ICIICE69672.2026.11565368.
[9]. X. Li, H. Li, C. Sun, Q. Fan, Z. Han, and V. C. M. Leung, “Edge-Enhanced Intelligence: A Comprehensive Survey of Large Language Models and Edge-Cloud Computing Synergy,” *IEEE Commun. Surveys Tuts.*, vol. 28, pp. 1248–1284, 2026, doi: 10.1109/COMST.2025.3587225.
[10]. W. U. Khan *et al.*, “Multi-Modal Foundation Models for Space-Air-Ground Integrated 6G and Beyond Networks: A Survey and Tutorial,” *IEEE Open J. Commun. Soc.*, vol. 7, pp. 4623–4659, 2026, doi: 10.1109/OJCOMS.2026.3687570.
[11]. M. Ferdowsi, N. Moustafa, M. Keshk, and B. Turnbull, “Trustworthy Intelligence: Split Learning-Embedded Large Language Models for Smart IoT Healthcare Systems,” *Electronics*, vol. 15, no. 7, p. 1519, Apr. 2026, doi: 10.3390/electronics15071519.
[12]. Z. Yang *et al.*, “Generative AI for Wireless Communication and Sensing: Toward Unified Foundation Models,” *IEEE Trans. Commun.*, vol. 74, pp. 10510–10539, 2026, doi: 10.1109/TCOMM.2026.3704192.
[13]. K. Jha and A. Jain, “Tiny-Transformer Based Multimodal Biometric Authentication with Edge Fusion and Federated Split Learning,” *Signal Image Video Process.*, vol. 20, no. 8, Jun. 2026, doi: 10.1007/s11760-026-05521-0.
[14]. J. Li *et al.*, “Integration of Generative AI and Mobile Networking: A Comprehensive Survey,” *IEEE Trans. Netw. Sci. Eng.*, vol. 13, pp. 4369–4405, 2026, doi: 10.1109/TNSE.2025.3639401.
[15]. Y. Zhang, “A Resource-Aware Multi-Fidelity Optimization Framework for Multimodal Music Information Analysis,” *IETE Tech. Rev.*, pp. 1–20, Jul. 2026, doi: 10.1080/02564602.2026.2692719.
[16]. C. Paduraru, M. Zavelca, and A. Stefanescu, “Agentic AI for Behavior-Driven Development Testing Using Large Language Models,” in *Proc. 17th Int. Conf. Agents and Artificial Intelligence (ICAART)*, 2025, pp. 805–815, doi: 10.5220/0013374400003890.

Publisher’s note: The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations. The content is solely the responsibility of the authors and does not necessarily reflect the views of the publisher.

ISSN (Online): 3105-9082