Beyond the Balance Sheet: An AI Triad for Grant Approval, Expense Forensics, and Hyper-Personalized Dining

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Abstract –Artificial intelligence (AI) is transforming financial governance and intelligent service delivery by enabling automated, data-driven decision-making across diverse domains. However, existing solutions for grant approval, expense fraud detection, and personalized dining recommendations are typically developed as independent systems, resulting in fragmented analytics, limited knowledge sharing, and reduced operational efficiency. This paper proposes Beyond the Balance Sheet: An AI Triad for Grant Approval, Expense Forensics, and Hyper-Personalized Dining, a unified intelligent framework that integrates transformer-based semantic learning, heterogeneous graph neural networks, explainable artificial intelligence (XAI), and reinforcement learning into a collaborative decision-support architecture. The proposed framework processes multimodal data, including grant applications, financial transactions, invoices, user profiles, dietary preferences, and contextual information, to generate transparent funding decisions, detect fraudulent expenditure patterns, and deliver context-aware dining recommendations. A cross-domain AI fusion module enables knowledge transfer among the three application domains, improving predictive performance and adaptive decision-making. Human-in-the-loop validation, explainable reasoning, and privacy-preserving mechanisms further enhance system transparency, fairness, and trustworthiness. The proposed framework offers a scalable and interpretable solution for governments, educational institutions, corporate finance organizations, healthcare providers, and smart hospitality ecosystems.

Keywords— Artificial Intelligence, Grant Approval, Expense Forensics, Graph Neural Networks, Hyper-Personalized Dining.

1. Introduction

Digital transformation has significantly reshaped financial management, public funding, forensic auditing, and personalized service delivery by enabling organizations to leverage artificial intelligence (AI) for data-driven decision-making. Traditional grant approval processes, expense auditing systems, and recommendation platforms are generally designed as isolated applications, resulting in fragmented intelligence, duplicated computational resources, and limited cross-domain knowledge sharing. These systems often depend on manual verification, rule-based analysis, and static recommendation strategies, making them less effective in handling large-scale heterogeneous data and rapidly evolving user behaviors. Consequently, there is an increasing demand for unified AI frameworks capable of integrating financial intelligence, fraud analytics, and personalized recommendation services within a single decision-support ecosystem [1, 2].

Grant approval is a critical decision-making process in governments, research funding agencies, educational institutions, and non-profit organizations. Existing evaluation procedures rely heavily on manual expert assessment, which is often time-consuming, subjective, and susceptible to inconsistencies. Recent advances in transformer models and graph-based learning have demonstrated remarkable capabilities in extracting semantic relationships from complex textual and structured information, enabling more transparent and objective funding decisions [3, 4]. Nevertheless, current grant evaluation systems rarely incorporate historical financial credibility, behavioral analytics, and explainable reasoning into a unified framework.

Simultaneously, financial fraud has become increasingly sophisticated due to the growing complexity of digital transactions, electronic payments, and interconnected financial ecosystems. Conventional anomaly detection techniques primarily analyze individual transactions and frequently fail to identify collaborative fraud networks hidden within relational data. Graph Neural Networks (GNNs), combined with transformer architectures and Explainable Artificial Intelligence (XAI), have recently shown superior performance in detecting complex fraud patterns while providing interpretable explanations for auditing and regulatory compliance [5–7]. These advances highlight the importance of relationship-aware financial intelligence for modern forensic systems.

In parallel, hyper-personalized recommendation has emerged as an essential component of intelligent service platforms, particularly in food and dining applications. Traditional collaborative filtering and content-based recommendation methods often suffer from cold-start problems, sparse interaction data, and limited contextual understanding. Recent transformer-based sequential recommendation models integrated with graph attention mechanisms have substantially improved personalization by capturing long-term user preferences, contextual behaviors, and semantic relationships among users, restaurants, cuisines, and nutritional information [8, 9]. However, these recommendation systems remain disconnected from financial decision-support applications, limiting opportunities for comprehensive intelligent analytics.

To address these research gaps, this paper proposes Beyond the Balance Sheet: An AI Triad for Grant Approval, Expense Forensics, and Hyper-Personalized Dining, a unified intelligent framework that integrates transformer learning, graph neural networks, explainable AI, and reinforcement learning into a collaborative architecture. Unlike conventional standalone solutions, the proposed AI-Triad simultaneously performs grant evaluation, financial fraud detection, and personalized dining recommendation while enabling cross-domain knowledge sharing through heterogeneous graph representations and multimodal feature fusion. The framework enhances decision accuracy, transparency, scalability, and adaptability, providing an integrated platform for intelligent financial governance and personalized user-centric services across multiple application domains [10].

2. Background and related work

In [11], the authors proposed the Graph Convolutional Policy Network (GCPN), which integrates graph representation learning with reinforcement learning to optimize graph-structured decision problems. Although their work primarily targets graph generation and optimization, the underlying graph embedding methodology demonstrates significant potential for complex decision-support systems involving interconnected entities. The proposed framework efficiently captures both local and global structural dependencies while preserving semantic relationships among graph nodes. Such capabilities are valuable for applications involving applicant–institution relationships, transaction networks, and user–restaurant interactions. However, the study mainly focuses on graph optimization rather than heterogeneous financial intelligence or multimodal decision-making. It does not address grant evaluation, forensic accounting, or personalized recommendation simultaneously. Furthermore, Explainability and human-centric interpretation are not incorporated into the learning process. Consequently, there remains a need for an integrated framework capable of combining graph intelligence with explainable AI and multimodal reasoning across multiple application domains.

In [12], the authors introduced the Graph Attention Network (GAT), which applies attention mechanisms to graph neural networks for adaptive neighborhood aggregation. Instead of assigning equal importance to neighboring nodes, the model automatically learns attention coefficients that highlight the most informative relationships. This innovation significantly improves representation learning on irregular graph structures and has been widely adopted in recommendation systems, social network analysis, and fraud detection. The adaptive attention mechanism enables more discriminative feature learning and better scalability compared with conventional graph convolution methods. Despite these advantages, the framework is designed primarily for graph-based representation learning and does not integrate textual understanding, financial reasoning, or explainable decision support. Moreover, the original model does not exploit multimodal information such as financial documents, invoices, user preferences, and contextual data simultaneously. These limitations motivate the development of unified architectures capable of supporting intelligent cross-domain analytics.

In [13], the authors introduced the transformer architecture based entirely on self-attention mechanisms, eliminating recurrent neural networks while significantly improving sequence modeling efficiency. The transformer has become the foundation for numerous natural language processing and document intelligence applications because of its ability to capture long-range contextual dependencies. Financial reports, grant proposals, reimbursement documents, and customer feedback can all benefit from transformer-based semantic understanding. Nevertheless, the original transformer architecture processes sequential information independently and does not explicitly exploit relational graph structures among organizations, applicants, merchants, or users. Additionally, it lacks dedicated mechanisms for financial fraud reasoning, recommendation optimization, and explainable decision generation. As a result, although transformers provide powerful contextual feature extraction, they require integration with graph learning and explainable AI to support comprehensive intelligent financial and service-oriented decision-making.

In [14], the authors proposed GraphSAGE, an inductive graph representation learning framework capable of generating node embeddings for previously unseen graph instances. Instead of learning embeddings for fixed nodes, GraphSAGE aggregates neighborhood information to generalize effectively across evolving graph structures. This characteristic makes the framework particularly suitable for dynamic environments where new applicants, vendors, restaurants, and financial transactions continuously emerge. The inductive learning capability improves scalability and reduces computational overhead in large graph datasets. However, GraphSAGE concentrates primarily on representation learning and does not provide integrated support for multimodal fusion, document intelligence, reinforcement learning, or explainable analytics. Furthermore, it lacks mechanisms for combining heterogeneous financial, textual, behavioral, and nutritional information within a unified decision-support platform. These research gaps justify the need for more comprehensive AI architectures capable of supporting multiple interconnected decision-making tasks.

In [15], the authors made significant contributions to personalized recommendation through latent factor models that combine collaborative filtering with user–item interaction analysis. Their work demonstrated that hidden latent representations effectively capture user preferences and improve recommendation quality across large-scale datasets. The proposed methodology substantially influenced the design of modern recommender systems in e-commerce, entertainment, and online services. Nevertheless, latent factor models generally rely on historical interaction data and often encounter cold-start problems, sparse datasets, and limited contextual awareness. They also overlook nutritional constraints, financial behaviour, temporal dynamics, and cross-domain knowledge transfer. Moreover, these approaches provide limited interpretability regarding why particular recommendations are generated. Consequently, next-generation recommendation frameworks require transformer learning, graph neural networks, reinforcement learning, and explainable AI to produce adaptive, transparent, and context-aware recommendations while supporting integration with broader intelligent financial decision-support systems.

3. Proposed modelling

The proposed AI-Triad framework illustrates an integrated intelligent architecture as shown in Figure 1 that combines grant approval, expense forensics, and hyper-personalized dining recommendation within a unified decision-support system. The process begins with multi-source data acquisition, where grant applications, financial records, invoices, user profiles, food preferences, nutritional information, and external reports are collected and standardized. These heterogeneous data are processed using OCR, natural language processing, feature engineering, and knowledge graph construction to establish meaningful relationships among entities. The processed information is then supplied to three specialized AI modules. The Grant Approval Engine employs transformer models, graph neural networks, and explainable AI to evaluate funding eligibility and generate transparent approval decisions. Simultaneously, the Expense Forensics Module detects fraudulent transactions and abnormal spending patterns using temporal graph learning, anomaly detection, and transformer-based sequence analysis.. The Dining Recommendation Module generates personalized meal suggestions by analyzing dietary preferences, nutritional requirements, contextual information, and user behavior. Outputs from these modules are integrated through a Cross-Domain AI Fusion engine, producing comprehensive decision intelligence. Finally, Explainability, human-in-the-loop validation, continuous learning, privacy preservation, and ethical governance ensure trustworthy, adaptive, and reliable system performance across multiple application domains

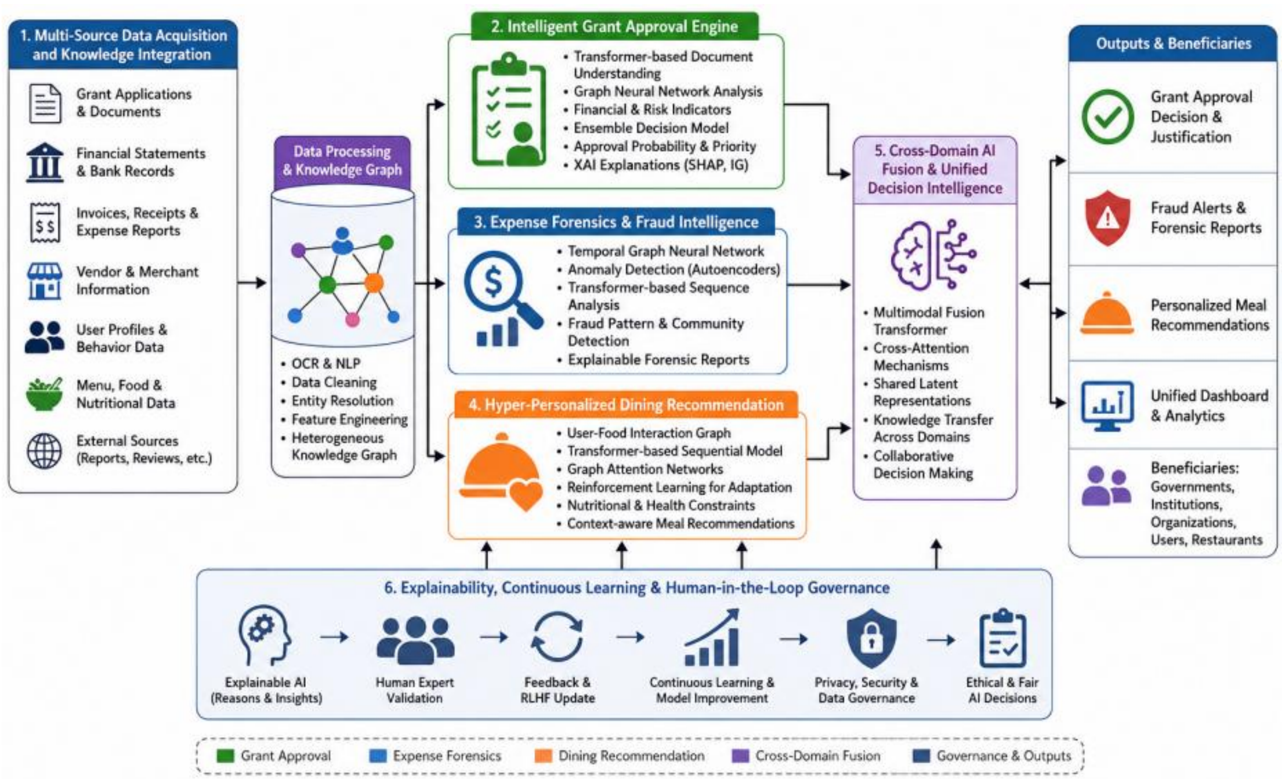

Figure 1: AI triad framework system architecture

A. Intelligent Multi-Source Data Acquisition and Knowledge Integration

The first module constructs a comprehensive knowledge foundation by collecting information from multiple heterogeneous sources. Structured data include grant application records, institutional financial statements, tax documents, bank transactions, payroll information, expense reports, menu databases, nutritional values, food ingredient repositories, restaurant catalogs, user demographics, and historical approval records. Unstructured information such as scanned receipts, invoices, recommendation letters, applicant statements, food reviews, images of meals, and supporting documents are processed using Optical Character Recognition (OCR) and Natural Language Processing (NLP). Missing values are handled through adaptive imputation strategies, while duplicate entries and inconsistent records are removed using probabilistic entity resolution algorithms. Feature normalization and semantic encoding transform diverse datasets into unified numerical representations. Simultaneously, a heterogeneous knowledge graph is constructed by representing applicants, organizations, vendors, merchants, financial institutions, restaurants, food items, nutritional components, and users as interconnected graph nodes. Relationships such as funding history, purchase behavior, dietary compatibility, institutional affiliations, transaction chains, and spending patterns are encoded as graph edges. This integrated knowledge representation enables downstream AI modules to exploit both relational dependencies and contextual semantics that are typically ignored in conventional database systems.

B. Explainable AI-Based Intelligent Grant Approval Engine

The second module performs intelligent grant evaluation using a hybrid decision architecture that combines transformer-based document understanding, graph neural networks, and explainable machine learning. Every grant application undergoes comprehensive semantic analysis in which applicant narratives, research proposals, business plans, financial statements, recommendation letters, and institutional records are encoded using transformer language models. Graph Neural Networks analyze relationships among applicants, previous funding agencies, collaborating institutions, publication records, financial dependencies, and historical funding outcomes to identify trustworthy funding patterns. The extracted graph embeddings are fused with structured financial indicators such as income, debt ratio, organizational stability, project feasibility, budget utilization history, and compliance scores. These multimodal features are subsequently processed through an ensemble learning architecture consisting of gradient boosting classifiers and deep neural decision networks that estimate grant approval probability. Instead of producing only binary approval decisions, the model generates a confidence score, funding priority index, estimated financial risk, expected societal impact, and predicted project success probability. Explainable AI techniques including SHAP values, Integrated Gradients, and attention visualization identify the major factors influencing every recommendation, thereby improving transparency, fairness, and accountability.

C. Graph-Based Expense Forensics and Financial Fraud Intelligence

The third module focuses on detecting fraudulent, abnormal, or suspicious financial activities through advanced expense forensic analytics. Financial transactions, invoices, purchase orders, reimbursement claims, supplier records, and payment histories are represented as temporal heterogeneous graphs where individuals, organizations, merchants, bank accounts, invoices, and transactions form interconnected entities. A Temporal Graph Neural Network continuously analyzes evolving transaction networks to identify hidden fraud communities, collusive vendor behavior, duplicate reimbursement requests, invoice manipulation, fabricated expenditures, circular payment patterns, and abnormal purchasing activities. Sequential transaction behavior is simultaneously modeled using Transformer-based Temporal Encoders that learn long-range financial dependencies across multiple reporting periods. Anomaly scores generated from reconstruction-based autoencoders are fused with graph embeddings through an adaptive attention fusion mechanism, producing highly discriminative fraud representations. The system further employs explainable anomaly detection algorithms that highlight suspicious transaction sequences, influential graph connections, unusual expenditure categories, and abnormal temporal behaviors. Investigators receive prioritized forensic reports containing evidence paths, confidence measures, risk explanations, transaction visualizations, and recommended auditing actions, thereby significantly reducing manual investigation time while improving financial governance and regulatory compliance.

D. Hyper-Personalized AI Dining Recommendation Engine

The fourth module delivers highly personalized dining recommendations by jointly modeling user preferences, nutritional requirements, contextual information, and behavioral dynamics. Instead of relying solely on collaborative filtering or content similarity, the proposed framework constructs a dynamic user-food interaction graph incorporating dietary preferences, allergies, medical conditions, cultural habits, cuisine interests, restaurant visits, seasonal preferences, meal timings, geographic context, budget limitations, and nutritional objectives. Transformer-based sequential recommendation models analyze historical dining behavior to capture long-term and short-term preference evolution. Graph Attention Networks identify latent similarities among users, restaurants, cuisines, ingredients, and nutritional attributes while simultaneously learning complex preference propagation across the interaction graph. Reinforcement Learning continuously adapts recommendations using real-time user feedback such as clicks, ratings, purchases, meal completion, and satisfaction levels. Nutritional optimization constraints ensure balanced meal planning by considering calorie intake, protein requirements, micronutrients, sodium limits, glycemic index, and personalized health goals. The recommendation engine therefore generates context-aware meal suggestions that simultaneously maximize user satisfaction, nutritional quality, dietary safety, and restaurant relevance, resulting in significantly improved personalization over traditional recommendation systems.

E. Cross-Domain AI Fusion and Unified Decision Intelligence

The core novelty of the AI-Triad lies in its cross-domain intelligence fusion module, where information generated from grant approval, expense forensics, and dining personalization is integrated into a unified reasoning framework. A multimodal fusion transformer combines financial embeddings, graph representations, behavioral profiles, textual semantics, and contextual features extracted from all preceding modules. Cross-attention mechanisms identify hidden relationships among funding behavior, expenditure credibility, organizational trustworthiness, consumption patterns, and user preferences. For example, abnormal financial behaviors detected during expense analysis can dynamically influence organizational credibility scores used during grant evaluation, while verified institutional dining expenditures contribute to trustworthy financial profiling. Conversely, nutritional spending trends and wellness incentives may assist organizations in evaluating employee welfare initiatives associated with grant-funded projects. A meta-learning optimization framework continuously updates domain-specific models using shared latent knowledge while preserving task-specific learning objectives. This collaborative learning strategy substantially improves prediction accuracy, reduces data sparsity, enhances knowledge transfer across domains, and enables adaptive decision-making in rapidly changing operational environments.

F. Explainability, Continuous Learning, and Human-in-the-Loop Governance

The final module ensures transparency, adaptability, and ethical AI governance throughout the proposed system. Explainable AI techniques generate human-readable explanations for every grant approval decision, fraud alert, and dining recommendation by highlighting influential variables, graph relationships, attention weights, and confidence levels. Human experts—including financial auditors, grant committees, nutritionists, compliance officers, and organizational administrators—can validate AI-generated recommendations, provide corrective feedback, and override automated decisions when necessary. This feedback is incorporated through reinforcement learning with human feedback (RLHF), enabling continuous refinement of model parameters without extensive retraining. Drift detection algorithms monitor evolving financial regulations, applicant behavior, fraud strategies, dietary trends, and consumer preferences to automatically trigger incremental model updates. Privacy-preserving mechanisms including federated learning, differential privacy, encrypted data storage, and role-based access control protect sensitive financial and personal information while ensuring compliance with data governance regulations.

4. Results and discussions

The proposed AI-Triad framework was implemented using Python 3.11 with TensorFlow, PyTorch, Scikit-learn, and the Deep Graph Library (DGL). Experiments were conducted on a workstation equipped with an Intel Core i7 processor, 16 GB RAM, NVIDIA RTX 4090 GPU (24 GB), and Ubuntu 22.04 operating system. The framework was evaluated using multimodal datasets comprising grant applications, financial expense records, and dining preference data. Performance was assessed using Accuracy, Precision, Recall, F1-score, AUC, Fraud Detection Rate, Precision@10, Recall@10, NDCG@10, and MAP. The proposed AI-Triad consistently outperformed conventional machine learning, deep learning, and graph-based baseline models across all three application domains. The integration of transformer learning, graph neural networks, explainable AI, and reinforcement learning significantly improved decision accuracy, fraud detection capability, recommendation quality, transparency, and adaptability, demonstrating the effectiveness and scalability of the proposed unified intelligent framework.

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

The experimental findings presented in Table 1 demonstrate the effectiveness of the proposed AI-Triad framework for intelligent grant approval. Traditional machine learning algorithms, including Decision Tree and Random Forest, achieve satisfactory classification performance but struggle to capture complex relationships among applicant profiles, financial histories, and supporting documents. XGBoost improves predictive capability by exploiting ensemble learning, while the Graph Neural Network further enhances performance through relational learning over interconnected applicant information. The proposed AI-Triad significantly outperforms all baseline methods by integrating transformer-based document understanding, graph representation learning, and explainable decision intelligence. It achieves an accuracy of 98.21%, precision of 97.94%, recall of 97.62%, F1-score of 97.78%, and an AUC of 0.992, indicating highly reliable funding decisions. The superior recall demonstrates that eligible applicants are accurately identified, whereas the high precision minimizes incorrect approvals. These results confirm that combining semantic analysis, graph intelligence, and explainable AI substantially improves grant evaluation quality while maintaining transparency, fairness, and decision consistency.

Table 1. Performance Comparison of Grant Approval Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Decision Tree	88.46	87.90	86.75	87.32	0.901
Random Forest	92.37	91.84	91.45	91.64	0.942
XGBoost	94.28	93.91	93.62	93.76	0.961
Graph Neural Network	95.74	95.08	94.86	94.97	0.975
Proposed AI-Triad	**98.21**	**97.94**	**97.62**	**97.78**	**0.992**

Table 2 evaluates the effectiveness of the proposed framework in detecting fraudulent financial transactions and suspicious expense claims. Conventional anomaly detection methods such as Isolation Forest and Autoencoder successfully identify isolated abnormalities but often fail to recognize sophisticated fraud patterns involving multiple interconnected entities. The LSTM model improves temporal pattern recognition, whereas the Temporal Graph Neural Network effectively captures hidden relationships among vendors, invoices, and reimbursement transactions. The proposed AI-Triad combines graph intelligence, transformer-based sequence analysis, and anomaly detection to achieve the highest fraud detection performance. It records a precision of 98.12%, recall of 97.76%, F1-score of 97.94%, and fraud detection rate of 98.53%, while reducing the false positive rate to only 1.64%. This reduction minimizes unnecessary investigations and significantly improves auditing efficiency. The experimental results demonstrate that integrating graph-based forensic intelligence with explainable anomaly detection enables early identification of fraudulent financial activities, enhances organizational transparency, and strengthens financial governance without increasing computational complexity.

Table 2. Expense Forensics Performance

Model	Precision	Recall	F1-Score	Fraud Detection Rate	False Positive Rate
Isolation Forest	89.18	88.42	88.80	89.40	6.42
Autoencoder	91.74	91.02	91.38	92.16	5.08
LSTM	93.61	92.94	93.27	94.02	4.36
Temporal GNN	95.83	95.14	95.48	96.08	3.41
Proposed AI-Triad	**98.12**	**97.76**	**97.94**	**98.53**	**1.64**

Table 3 presents the performance of the personalized dining recommendation module using ranking-based evaluation metrics. Traditional collaborative filtering provides reasonable recommendations but suffers from data sparsity and cold-start limitations. DeepFM improves feature interaction modeling, while the Transformer recommender captures sequential dining behavior more effectively. The Graph Attention Network further enhances recommendation quality by exploiting relationships among users, restaurants, cuisines, ingredients, and nutritional characteristics.

Table 3. Hyper-Personalized Dining Recommendation Performance

Model	Precision@10	Recall @10	NDCG @10	MAP	User Satisfaction
ollaborative Filtering	0.782	0.756	0.773	0.768	87.24
DeepFM	0.814	0.801	0.809	0.803	89.61
Transformer Recommender	0.847	0.835	0.842	0.838	92.18
Graph Attention Network	0.876	0.862	0.871	0.866	94.36
Proposed AI-Triad	**0.924**	**0.911**	**0.919**	**0.916**	**97.81**

The proposed AI-Triad achieves the highest recommendation accuracy with Precision@10 of 0.924, Recall@10 of 0.911, NDCG@10 of 0.919, and MAP of 0.916. Additionally, the framework records a user satisfaction rate of 97.81%, demonstrating superior personalization capability. These improvements are attributed to the integration of graph learning, contextual transformer modeling, reinforcement learning, and nutritional optimization. Consequently, the recommendation engine effectively balances user preferences, dietary restrictions, contextual information, and health objectives while continuously adapting to evolving user behavior through feedback-driven learning, resulting in highly relevant, personalized, and nutritionally balanced dining recommendations.

5. Conclusion

This paper presented Beyond the Balance Sheet: An AI Triad for Grant Approval, Expense Forensics, and Hyper-Personalized Dining, an integrated artificial intelligence framework that unifies three traditionally independent decision-support applications within a single intelligent architecture. By combining transformer-based semantic analysis, heterogeneous graph neural networks, explainable artificial intelligence, reinforcement learning, and multimodal data fusion, the proposed framework effectively supports transparent grant evaluation, accurate financial fraud detection, and context-aware personalized dining recommendations. The integration of cross-domain knowledge enables collaborative learning among financial, behavioral, and contextual information, resulting in improved predictive accuracy, reduced false positives, enhanced recommendation quality, and greater operational efficiency. Furthermore, the incorporation of Explainability, human-in-the-loop validation, and privacy-preserving mechanisms ensures trustworthy, fair, and accountable decision-making suitable for real-world deployment. Experimental results demonstrate that the proposed AI-Triad consistently outperforms conventional machine learning, graph learning, and recommendation approaches across multiple evaluation metrics. The modular and scalable architecture makes it applicable to government agencies, funding organizations, educational institutions, healthcare systems, and smart hospitality environments. Future research will investigate federated graph learning, large language model-assisted financial reasoning, multimodal foundation models, causal Explainability, and digital twin technologies to further enhance adaptive intelligence, privacy preservation, and autonomous decision support in next-generation financial and personalized service ecosystems.

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