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Article

Knowledge-Based Recommendation for Graduate Subject Allocation Using Graph Attention Networks (GAT)

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Abstract

This study proposes a hybrid artificial intelligence framework for graduate subject allocation that enhances fairness, transparency, and operational efficiency in higher education. By integrating rule-based reasoning with advanced deep learning models, the framework supports data-driven decision-making for academic suitability, workload equity, and research alignment, while embedding Explainable Artificial Intelligence (XAI) to facilitate digital transformation in Thai universities. Traditional subject allocation processes in graduate programs are often manual, time-consuming, and subject to subjective judgment, thereby limiting their capacity to adapt to increasing curricular complexity and diverse faculty profiles. To address these challenges, the proposed framework combines institutional knowledge-based rules with machine learning techniques to model complex academic relationships across faculty, subjects, and workloads. Empirical analysis was conducted using data from 480 faculty members at Mahasarakham University and evaluated using multiple predictive models, including XGBoost, Wide-and-Deep Neural Networks, and Graph Neural Networks. Faculty performance was assessed using 20 institutional indicators reflecting teaching experience, research productivity, supervision, administrative responsibilities, and digital pedagogical competence. A multi-objective ranking algorithm was applied to simultaneously optimize academic suitability, workload balance, and research-teaching alignment. To enhance transparency and usability, the system incorporates a Faculty Subject Allocation Dashboard (FSAD) with SHAP-based interpretability, enabling administrators to understand and validate allocation decisions in real time. The results demonstrate that the proposed framework significantly improves allocation accuracy, workload equity, and decision transparency, offering a scalable and explainable solution for AI-driven academic governance.

Keywords: knowledge-based recommendation; deep learning; graph neural network; faculty workload allocation; explainable AI; higher education management; multi-objective optimization

1. Introduction

In recent years, higher education institutions have faced growing complexity in curriculum design and subject allocation due to the rapid expansion of course offerings, interdisciplinary programs, and varied student profiles Duncombe (1959). At the same time, the advent of large-scale educational data (student records, faculty profiles, course metadata) creates opportunities to apply intelligent systems for decision support (Zhang et al. 2025). Recommendation systems (RSs) have emerged as crucial tools for filtering choices, suggesting alternatives, and guiding decision-making in high-dimensional, constrained domains (Zhang et al. 2026). In the educational domain, RSs have traditionally supported students (e.g., by recommending learning resources and courses) (Gomis et al. 2023). However, relatively few studies consider RSs in faculty workload and subject allocation,

which involve multiple stakeholders (students, faculty, programs) and hard constraints (prerequisites, scheduling, capacity). The need to allocate subjects optimally is especially pronounced in graduate studies, where curriculum progress, research alignment, and faculty specialization are of great importance (Su and Su 2025). Traditionally, subject allocation has been rule-based (program policies, prerequisites, faculty load), overseen by academic advisers and administrators. However, such manual systems have limitations: they may not account for latent factors such as faculty research alignment, student interest vectors, or the interplay among faculty-student-subject relationships (kuabe et al.2025). Meanwhile, advances in machine learning (ML) and deep learning (DL) offer greater capacity to model complex, relational, and higher-order structures (Ragab et al., 2025). Knowledge-graph-enhanced recommendation systems extend beyond traditional collaborative filtering and content-based methods by leveraging side information and relational embeddings, thus improving performance and explainability (Zhang 2025). For example, Graph Neural Networks (GNNs) applied to heterogeneous educational graphs (students, courses, faculty) have demonstrated superior ranking accuracy in course recommendations (Qu et al. 2024). In the context of subject allocation, these methods can encode faculty expertise, research output, student interests, program relationships, and scheduling constraints into one unified graph of entities and relations.

Despite these technical advances, there remains a gap in the application of hybrid frameworks to subject allocation at the graduate level. Most work focuses on recommending learning resources or courses to students rather than optimizing subject allocation decisions that involve faculty, program, and institutional constraints (Zhao 2025). Moreover, existing educational RS research often neglects faculty-centric factors (such as research productivity, mentoring quality, and digital pedagogy competence), which are salient in graduate subject allocation. Therefore, this study proposes a hybrid framework combining a curriculum knowledge base (encoding prerequisites, capacity, scheduling, faculty eligibility) with deep learning recommendation models (XGBoots, GNN, wide & deep) to generate optimal subject-faculty allocations in graduate studies. The key contributions are three-fold: (Duncombe 1959) design of a faculty-subject-program knowledge graph incorporating faculty competency and institutional rules; (F. Zhang et al. 2025) training of deep hybrid recommenders that predict suitability scores for subject allocation; (Y. Zhang et al. 2026) evaluation of the system in a real institutional context (~480 respondents across six faculties) to assess performance and interpretability. In the remainder of this paper, we review related work on educational recommendation systems, knowledge graph-based recommendations, and faculty workload allocation frameworks (Section II), describe the research methodology (Section III), present evaluation performances (Section IV), discuss experiment results for practice (Section V), and conclude with conclusions and future work (Section VI and VII).

2. Materials and Methods

Over the past decade, recommender systems (RSs) have evolved into core components of digital learning ecosystems, revolutionizing how universities deliver personalized education and make data-driven decisions across teaching, learning, and management processes [11]. In higher education, these systems form part of the broader shift toward Learning Analytics and Educational Data Mining frameworks, enabling the dynamic personalization of courses, resources, and learning trajectories for individual learners. Educational Recommender Systems (ERSs) are primarily designed to enhance learning experiences by filtering, ranking, and matching learning resources, instructors, and students within massive institutional databases (Kopyt et al. 2016). A growing body of research demonstrates their effectiveness in course recommendation, adaptive tutoring systems, e-learning resource curation, and student performance prediction, establishing ERSs as critical enablers of personalized, learner-centered education. However, systematic literature reviews reveal that, although ERSs have achieved significant success in instructional domains, their application to administrative and institutional processes remains limited, particularly in graduate education contexts (Fardel et al., 2007). Traditional subject allocation frameworks in higher education often rely on rule-based assignment or manual heuristic decision-making, constrained by static institutional policies, faculty

self-reports, or historical workload data (Comite and Pierdicca 2022). These methods tend to be less adaptable to evolving academic conditions, leading to mismatches between faculty expertise, student research interests, and institutional strategic goals. Such limitations demonstrate the growing need for intelligent, data-driven decision-support systems that can balance academic quality, workload fairness, and policy compliance. As universities adopt digital transformation and AI-enabled governance frameworks, integrating artificial intelligence (AI) and deep learning (DL) into subject allocation processes has emerged as a promising research frontier (Habi and Messer 2021).

Recent advancements in deep learning architectures (Neural Collaborative Filtering (NCF), Wide-and-Deep Neural Networks, and Graph Neural Networks (GNNs)) have significantly expanded the capacity of recommendation systems to learn latent representations and multi-relational patterns that traditional statistical models often fail to capture [16]. These models transcend simple input-output prediction by embedding semantic and structural relationships among diverse entities such as students, faculty, subjects, and institutional rules. In educational applications, such models enable reasoning over both explicit relationships (e.g., teaching history, research specialization) and implicit associations (e.g., mentoring effectiveness, digital teaching affinity). Knowledge Graphs (KGs) have further augmented this capability by structuring educational data into interconnected ontologies that allow semantic reasoning. Studies have shown that KG-based educational recommenders enhance adaptive learning pathways, dynamic course sequencing, and skill mapping—resulting in improved personalization and cognitive alignment between learners and content (Robillos 2024). However, despite these successes, the application of KGs and deep learning to academic management remains underexplored. Most prior works focus on student-side personalization, leaving institutional decision-making processes largely rule-driven and manually optimized. Recent hybrid frameworks that integrate knowledge-based reasoning with deep representation learning represent a transformative paradigm shift, combining the transparency of expert systems with the adaptability of neural models (Tang 2025). Such hybrid models can encode formal institutional constraints while simultaneously learning implicit patterns from historical data to improve fairness in allocation and predictive accuracy. Incorporating GNNs into educational recommendation architectures has proven particularly promising, as these models capture graph-structured dependencies across academic entities. GNNs enable joint optimization across heterogeneous nodes (faculty, subjects, programs) and their relational edges (e.g., expertise similarity, co-teaching, administrative linkage), leading to higher accuracy and explainability in recommendation outputs (Aziz 2025). Moreover, integrating reinforcement learning (RL) mechanisms enables these systems to adapt dynamically to policy shifts and feedback loops over time—supporting continuous learning and optimization in evolving academic environments. Systematic reviews further emphasize that explainability and fairness are emerging as fundamental design imperatives in educational AI, ensuring that algorithmic decisions uphold ethical standards, promote equity, and comply with accreditation requirements (Aina et al., 2024). In the context of faculty workload allocation, scholars have identified significant challenges in balancing quantitative factors (e.g., teaching experience, academic rank, and administrative duties) with qualitative indicators (e.g., mentoring quality, research supervision, and digital pedagogical skills) (Zhang 2025). Current decision models often fail to integrate these diverse dimensions holistically, resulting in inconsistent workload distribution and potential faculty dissatisfaction. Few frameworks treat the triadic relationship among faculty, subjects, and programs as a co-dependent decision space in which optimizing one dimension directly influences the others. Knowledge graph-enhanced hybrid recommender systems directly address this gap by enabling multi-objective optimization while preserving interpretable rule traces for administrative validation (Downing 2025). Empirical studies have demonstrated that combining domain ontologies and explicit workload constraints with neural learning architectures substantially improves both accuracy and transparency, making such systems well-suited for institutional deployment.

In summary, the existing literature provides compelling evidence for the potential of deep learning-based, knowledge-graph-augmented recommender systems to address complex

educational challenges. However, significant gaps remain regarding faculty-centric subject allocation, hybrid knowledge-driven optimization, and real-world validation within university environments. The present study aims to bridge these gaps by developing and evaluating a knowledge-based deep learning framework that integrates graph attention mechanisms, policy rule reasoning, and multi-objective optimization. This approach aspires to achieve optimized, equitable, and explainable subject allocation in graduate studies—transforming academic resource management into a transparent, data-driven, and institutionally aligned process that reflects the next stage of intelligent higher-education governance.

2.1. Research Objectives

The overarching goal of this research is to design and validate a knowledge-based deep learning framework that intelligently automates and optimizes subject allocation in graduate programs, ensuring fairness, transparency, and institutional alignment. Building on advances in Graph Attention Networks (GATs) and knowledge-based reasoning, the study seeks to transform the traditional rule-driven subject assignment process into a data-driven, interpretable, and adaptive decision-support system.

To achieve this overarching goal, the study is guided by the following specific objectives:

1. To design a hybrid knowledge-based GAT framework that integrates explicit institutional rules (e.g., qualification requirements, workload limits, supervision policies) with data-driven learning from historical allocation patterns.
2. To construct a comprehensive indicator–subject knowledge graph that captures semantic and relational dependencies among indicator members, subjects, research domains, and workload profiles, enabling contextual reasoning within the allocation process.
3. To develop a GAT-based allocation model that learns attention coefficients representing the importance of faculty indicators in predicting allocation suitability.
4. To apply multi-objective optimization techniques that balance allocation goals within a unified allocation function.
5. To evaluate the performance and interpretability of the proposed GAT model against benchmark algorithms (XGBoost, Wide-and-Deep Neural Network, and standard GNN) using key metrics such as Accuracy, F1-score, AUC, HR@10, and NDCG@10.
6. To design and implement an Indicator Subject Allocation Dashboard (ISAD) that translates model outputs into a usable decision-support interface, allowing administrators to visualize, validate, and adjust allocation outcomes in real time.
7. To validate the framework empirically using data from 480 respondents across six faculties at Mahasarakham University, assessing the system’s predictive accuracy, explainability, and institutional applicability.

3. Research Methodology

This study adopts a quantitative approach integrating knowledge-based reasoning, deep learning, and institutional data analysis to develop and evaluate a hybrid intelligent system for subject allocation in graduate studies. The overall research procedure comprises five sequential phases: 3.1 data collection process; 3.2 problem identification and data preparation; 3.3 deep learning model development; (D) training objective and regularization; and 3.4 validation and interpretation for institutional application.

3.1. Data Collection Process

Data were collected at Mahasarakham University, across six faculties (Science, Engineering, Information Technology, Humanities and Social Sciences, Mahasarakham Business School, and Education) to represent both the science and social science domains. A total of 480 respondents participated, selected through stratified random sampling to ensure proportional representation

across academic disciplines and ranks. Each respondent completed a structured questionnaire containing three parts: (1) demographic information (gender, age, academic rank, years of experience, department), (2) twenty (20) measurable variables related to factors influencing subject allocation, and (3) institutional engagement outcomes such as research contribution and teaching workload perception. All 20 features were defined quantitatively as follows: Teaching Experience (years) (F₁), Academic Qualification (highest degree) (F₂), Designation (academic rank) (F₃), Number of Subjects Taught (F₄), Research Productivity (F₅), Administrative Responsibility (F₆), Academic Outcome Achievement (F₇), Admission and Recruitment Contribution (F₈), Training and Placement Involvement (F₉), Accreditation and Documentation Handling (F₁₀), Examination and Evaluation Contribution (F₁₁), Institutional and Club Engagement (F₁₂), Value and Ethics Participation (F₁₃), Professional Society Membership (F₁₄), Cultural and Community Outreach (F₁₅), Event Coordination Beyond Institute (F₁₆), Undergraduate Project Mentorship (F₁₇), Postgraduate/Ph.D. Supervision (F₁₈), Student Mentorship and Guidance (F₁₉), and Digital Pedagogical Competence (F₂₀). The 20 indicators used in the subject allocation model in this study are listed in Table 1 (Saxena et al. 2023).

Table 1. 20 Indicators input for the subject allocation model.

Code	Variable Name	Description and Measurement Aspect	Functional Role in Model
F ₁	Teaching Experience	Total years of full-time teaching at the university level	Contributes to expertise and stability assessment
F ₂	Academic Qualification	Highest degree attained (Master's/Ph.D.)	Eligibility and policy compliance check
F ₃	Designation / Academic Rank	Faculty position (Lecturer, Assistant, Associate, Professor)	Seniority and teaching-level suitability
F ₄	Number of Subjects Taught	Count of distinct courses handled per semester	Teaching versatility and workload indicator
F ₅	Research Productivity	Annual research output (Scopus/TCI publications, grants, projects)	Predictor of research-teaching alignment
F ₆	Administrative Responsibility	Leadership or management roles held (e.g., Head, Dean, Coordinator)	Penalized feature for workload balancing
F ₇	Academic Outcome Achievement	Improvement in student learning outcomes or course evaluations	Measures teaching effectiveness and quality
F ₈	Admission Contribution	Role in student recruitment or admissions processes	Institutional engagement factor
F ₉	Training and Placement Contribution	Participation in student training, internships, or placement programs	Applied or industry engagement indicator
F ₁₀	Accreditation/ Documentation Handling	Involvement in preparing accreditation or QA documentation	Reflects the administrative workload burden
F ₁₁	Examination and Evaluation Contribution	Role in examination committees, grading, or assessment	Core teaching-support responsibility
F ₁₂	Club / Institutional Innovation Engagement	Participation in innovation councils or academic clubs	Indicator of extracurricular academic activity
F ₁₃	Value and Ethics Education Participation	Engagement in moral, social, or ethical training programs	Reflects contribution to holistic education
F ₁₄	Professional Society Membership	Active membership in recognized professional bodies	Reflects subject-domain professional affiliation

F ₁₅	Cultural and Community Engagement	Participation in social, cultural, or community events	Adds diversity and social-engagement dimension
F ₁₆	Event Coordination Beyond the Institute	Involvement in events under university/state/national agencies	Reflects leadership and outreach visibility
F ₁₇	Undergraduate Project Mentorship	Number of undergraduate research or project supervisions	Proxy for academic mentoring experience
F ₁₈	Postgraduate/ Ph.D. Supervision	Number of ongoing or completed postgraduate theses supervised	High-impact variable for graduate-level allocation
F ₁₉	Student Mentorship and Guidance	Assigned role as academic or personal mentor to students	Student support and engagement indicator
F ₂₀	Digital Pedagogical Competence	Proficiency in LMS, e-learning, AI tools, and online pedagogy	Top-ranked predictor for digital teaching readiness

3.2. Problem Identification and Data Preparation

The dataset for this study comprised 480 data points collected from six faculties at Maha Sarakham University. Each respondent was characterized by 20 indicators (F₁–F₂₀), covering experience, qualification, designation, research productivity, administrative load, mentorship, and digital competence. The raw dataset underwent a multi-stage preprocessing pipeline to ensure completeness, consistency, and suitability for training a Graph Attention Network (GAT). The ten-step process is summarized below, along with practical outcomes.

Step 1: Missing-Value Imputation: Approximately 4.7% of the entries contained missing values, primarily in F₁ (Teaching Experience), F₄ (Subjects Taught), and F₅ (Research Productivity). For numeric features, mean imputation was applied using Eq. (1).

$$x'_i = \begin{cases} x_i, & \text{if } x_i \neq \text{NaN} \\ \frac{1}{n} \sum_{k=1}^n x_k, & \text{if } x_i = \text{NaN} \end{cases} \tag{1}$$

For categorical variables (e.g., F₂ Academic Qualification, F₃ Designation), mode imputation replaced missing entries, which is defined as Eq. (2) [24].

$$x'_i = \text{mode}(x_1, x_2, \dots, x_n) \tag{2}$$

After imputation, the proportion of missing values was reduced from 4.7% to 0%, ensuring data completeness across all 20 features.

Step 2: Data Normalization (Min–Max Scaling): To ensure numerical stability and prevent dominance of high-magnitude variables, continuous indicators (F₁, F₄, F₅, F₇, F₁₈) were scaled to the [0, 1] interval using Eq. (3) [25].

$$x_i^{\text{norm}} = \frac{x_i - \min}{x_{\max} - x_{\min}} \in [0, 1] \tag{3}$$

For example, F₁ (Teaching Experience) ranged from 2 to 40 years, resulting in Eq. (4).

$$x_i^{\text{norm}} = \frac{20 - 2}{40 - 2} = 0.47 \tag{4}$$

This standardization improved convergence stability during neural optimization and reduced skewness by 64%.

Step 3: Categorical Encoding: Categorical variables (F₂ (Qualification), F₃ (Designation), and F₁₄ (Professional Society)) were numerically transformed for model interpretability. Label encoding assigns ordinal values as defined in Eq. (5) [26].

$$\text{Ph.D.} = 3, \text{Master} = 2, \text{Bachelor} = 1 \tag{5}$$

For multi-class categories (e.g., Lecturer, Assistant Professor, Associate Professor, Professor), One-Hot Encoding was applied using Eq. (6).

$$\text{Designation} = [1\ 0\ 0\ 0] (\text{Lectuer}), [0\ 0\ 1\ 0] (\text{Associate Professor}) \quad (6)$$

This produced six categorical vectors, which were subsequently transformed into 64-dimensional embeddings for GAT input.

Step 4: Outlier Detection and Capping: To mitigate the influence of extreme values, the Interquartile Range (IQR) method was applied, as defined in Eq. (7).

$$\begin{aligned} \text{IQR} &= Q_3 - Q_1, \\ x_i^{\text{capped}} &= \begin{cases} Q_3 + 1.5(\text{IQR}), & \text{if } x_i > Q_3 + 1.5(\text{IQR}) \\ Q_1 + 1.5(\text{IQR}), & \text{if } x_i < Q_1 - 1.5(\text{IQR}) \\ x_i & \text{otherwise} \end{cases} \quad (7) \end{aligned}$$

For example, F_5 (Research Productivity) had $Q_1 = 4.0$, $Q_3 = 12.0$, yielding $\text{IQR} = 8.0$. The upper bound $= 12 + 1.5(8) = 24$, so any publication count > 24 was capped at 25.

This reduced the skewness of outliers from 1.72 to 0.63.

Step 5: Correlation and Multicollinearity Analysis: A Pearson correlation matrix was computed using Eq. (8) [27].

$$r_{xy} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}} \quad (8)$$

Features exceeding $|r_{xy}| > 0.90$ were considered multicollinear. F_6 (Administrative Responsibility) and F_{10} (Accreditation Handling) initially showed $r = 0.93$. After transformation (weighted mean composite adjustment), r dropped to 0.72, mitigating redundant signal propagation in GAT.

Step 6: Feature Embedding Preparation: Encoded categorical variables (F_2, F_3, F_{14}) were projected into a 64-dimensional latent space, as defined in Eq. (9) [28].

$$E = W_e X + b_e \quad (9)$$

where $W_e \in \mathbb{R}^{64 \times d}$ and b_e are trainable embedding parameters. This transformation preserved semantic relationships between categories while providing dense vector inputs for the GAT attention layer.

Step 7: Knowledge-Based Filtering: To align the data with university policies, eligibility rules were applied using Eq. (10) [27].

$$\begin{aligned} &\text{If}(F_2 < \text{Ph.D.}) \text{ and } (\text{CourseLevel} = \text{Graduate}) \\ &\Rightarrow \text{Remove Sample} \end{aligned} \quad (10)$$

From 480 records, 17 were removed for lacking doctoral qualifications or holding administrative exemptions, leaving 463 valid respondents. This ensures compliance with Mahasarakham University's graduate-teaching criteria.

Step 8: Workload Normalization: Workload was standardized to institutional averages using Eq. (11).

$$W'_i = \frac{W_i - \bar{W}}{\sigma W} \quad (11)$$

where $\bar{W} = 10.6$ hours and $\sigma W = 3.2$. Post-normalization, the mean workload equaled 0.00 (SD = 1.0), and extreme load deviations (> 2 SD) were corrected using a clipping function $\min(\max(W'_i, -2), 2)$, improving fairness consistency across faculty profiles.

Step 9: Data Augmentation and Balancing: To mitigate data imbalance (class ratio of 3.4:1), the Synthetic Minority Over-Sampling Technique (SMOTE) was employed, as described in Eq. (12) [29].

$$x_{\text{new}} = x_i + \lambda(x_{\text{mn}} - x_i) \quad (12)$$

Synthetic faculty–subject samples were generated for underrepresented disciplines, increasing the total number of instances from 2,450 to 3,200 (≈27% increase). This adjustment improved the GAT model’s class-balance F1-score from 0.812 to 0.871 during pilot validation.

Step 10: Final Graph Construction for GAT Input: The cleaned and enriched dataset was converted into a bipartite graph, as defined in Eq. (13).

$$\begin{aligned} G &= (V, E), V = F \cup S, |F| = 463, \\ |S| &= 320, |E| = 9,850 \end{aligned} \tag{13}$$

Edges $e_{ij} = (f_i, s_j)$ were weighted by suitability, defined as in Eq. (14).

$$\begin{aligned} w_{ij} &= \alpha_1 \cdot F_5^{\text{norm}} + \alpha_2 \cdot F_{18}^{\text{norm}} \\ &+ \alpha_3 \cdot F_{20}^{\text{norm}} + \alpha_4 \cdot (1 - |W'_i|) \end{aligned} \tag{14}$$

with weight parameters $(\alpha_1, \alpha_2, \alpha_3, \alpha_4) = (0.35, 0.25, 0.25, 0.15)$ with weight parameters $A \in \mathbb{R}^{783 \times 783}$ was used as the input topology for the Graph-Attention Network (GAT), ensuring attention coefficients α_{ij} could be learned across all 20 features. The outputs of the data preparation pipeline are applied before training the GAT model for knowledge-based subject allocation in graduate studies, as shown in Table 2.

Table 2. Results after the data preparation process.

Data Preprocessing	Description of Process	Affected Features	Before Processing	After Processing	Remarks / Outcome
1. Missing-Value Imputation	Applied mean imputation for numerical features and mode for categorical variables	F1–F4, F5, F6, F10	4.7% missing values	0% missing values	Data completeness achieved
2. Data Normalization (Min–Max Scaling)	Normalized continuous variables into [0,1] range for neural compatibility	F1 (Experience), F5 (Research), F7, F18	Range (0–40 years or counts)	Normalized (0.00–1.00)	Prevented dominance of large-scale features
3. Categorical Encoding (One-Hot / Label Encoding)	Encoded categorical variables (e.g., Qualification, Designation) as numeric vectors	F2, F3, F14	6 text categories	6 encoded vectors	Ensured model interpretability
4. Outlier Detection and Capping	Used the IQR method to cap extreme values above Q3+1.5IQR	F5 (Publications), F18 (Supervision)	Max = 38	Adjusted Max = 25	Stabilized training data distribution
5. Correlation and Multicollinearity Analysis	Removed redundant features ($r > 0.90$) to improve model convergence	F6 vs. F10	$r = 0.93$	$r = 0.72$ after removal	Enhanced independence between predictors
6. Feature Scaling and Embedding Preparation	Embedded categorical variables into 64-dimensional vectors	F2, F3, F14	Raw categorical indices	64-D embeddings	Prepared for GAT input layer
7. Knowledge-Based Filtering (Eligibility Rules)	Removed ineligible records (non-Ph.D. teaching graduate courses)	F2 (Qualification), F3 (Rank)	$n = 480$ respondents	$n = 463$ valid respondents	Aligned the dataset with the academic policy

8. Workload Normalization	Adjusted faculty teaching hours to the institutional mean load	F ₄ (Subjects), F ₆ (Admin) Mean = 10.6 hrs	Adjusted mean = 8.3 hrs	Balanced workload representation
9. Data Augmentation (Cross-Sectional Balancing)	Generated synthetic faculty–subject pairs for underrepresented fields using SMOTE	F ₅ –F ₁₈ 2,450 samples	3,200 samples	Reduced data imbalance by 27%
10. Final Graph Construction for GAT	Built a bipartite adjacency matrix and feature embeddings	All F ₁ –F ₂₀ -	Graph size = (463 faculty × 320 subjects)	Input-ready dataset for GAT training

3.3. Deep-Learning Model Development

1) Gradient-Boosted Trees (XGBoost; Tabular Baseline) The Gradient-Boosted Decision Trees (GBDT) algorithm, implemented via Extreme Gradient Boosting (XGBoost), was adopted as the baseline machine-learning model for tabular data due to its robustness, interpretability, and ability to model non-linear relationships among multiple faculty performance factors and subject-allocation suitability (Zhang, 2025). XGBoost constructs an additive ensemble of regression trees, where each successive tree attempts to correct the residual errors of the preceding ensemble. Formally, given a training dataset as Eq. (Habi and Messer 2021).

$$D = \left\{ (u_{ij}, \alpha_{ij}) \right\}_{i,j=1}^N, \quad (15)$$

where $u_{ij} \in \mathbb{R}^d$ represents the concatenated feature vector derived from faculty x_{f_i} , subject y_{s_j} , and pairwise characteristics and $\alpha_{ij} \in \{0, 1\}$ is the binary label indicating whether faculty f_i was historically assigned to subject s_j . The model predicts a suitability score $\hat{y}_{ij}$ through an ensemble of K additive functions, which is defined as Eq. (16).

$$\hat{y}_{ij} = \sigma \left(\sum_{k=1}^K f_k(u_{ij}) \right), f_k \in F, \quad (16)$$

At the t th boosting iteration, the model adds a new tree f_t that minimizes the regularized objective defined by Eq. (18).

$$L^{(t)} = \sum_{(i,j)} \ell(\alpha_{i,j}, \hat{y}_{ij}^{(t-1)} + f_t(u_{ij})) + \Omega(f_t), \quad (18)$$

where $\ell(\alpha, \hat{y})$ is the differentiable convex loss function, which is defined as Eq. (19).

$$\ell(\alpha_{ij}, \hat{y}_{ij}) = -[\alpha_{ij} \log y_{ij} + (1 - \alpha_{ij}) \log(1 - y_{ij})], \quad (19)$$

and $\Omega(f_t)$ is the regularization term controlling tree complexity, which is defined by Eq. (20).

$$\Omega(f_t) = \ell T_t + \frac{1}{2} \lambda \sum_{t=1}^{T_t} w_t^2, \quad (20)$$

where T_t is the number of leaves in the tree, γ penalizes additional leaves (model complexity), and λ enforces L2-regularization on leaf weights. To efficiently optimize $L^{(t)}$, a second-order Taylor expansion of the loss around $\hat{y}_{ij}^{(t-1)}$ is employed using Eq. (21).

$$L^{(t)} \approx \sum_{(i,j)} \left[g_{ij} f_t(u_{ij}) + \frac{1}{2} h_{ij} f_t^2(u_{ij}) \right] + \Omega(f_t) \quad (21)$$

where $g_{ij} = \partial_{\hat{y}} \ell(\alpha_{ij}, \hat{y}_{ij}^{(t-1)})$ and $h_{ij} = \partial_{\hat{y}}^2 \ell(\alpha_{ij}, \hat{y}_{ij}^{(t-1)})$ are the first and second-order gradients with respect to predictions. For a given tree structure q , the optimal weight for each leaf t is derived as Eq. (22).

$$w_t^* = - \frac{\sum_{(i,j) \in I_t} g_{ij}}{\sum_{(i,j) \in I_t} h_{ij} + \lambda}, \quad (22)$$

and the corresponding optimal objective reduction (gain) achieved by splitting a node is defined as Eq. (23).

$$\text{Gain} = \frac{1}{2} \left[\frac{\left(\sum_{(i,j) \in I_L} g_{ij} \right)^2}{\sum_{(i,j) \in I_L} h_{ij} + \lambda} + \frac{\left(\sum_{(i,j) \in I_R} g_{ij} \right)^2}{\sum_{(i,j) \in I_R} h_{ij} + \lambda} - \frac{\left(\sum_{(i,j) \in I} g_{ij} \right)^2}{\sum_{(i,j) \in I} h_{ij} + \lambda} \right] - \gamma, \quad (23)$$

where IL and IR denote left and right branches after the split. Splits with the highest positive Gain values are greedily selected, leading to an efficient, regularized, and scalable ensemble.

2) Wide-and-Deep Neural Network (WDNN) (Tabular Deep Learning + Cross Features)

The Wide-and-Deep Neural Network (WDNN) model is a hybrid deep-learning approach that combines memorization of explicit feature interactions (wide component) with generalization via non-linear transformations (deep component), making it highly effective for heterogeneous tabular data such as faculty attributes, subject descriptors, and institutional indicators (Saxena et al., 2023).

The model's input vector $u_{ij} \in \mathcal{R}^d$ represents the concatenation of normalized faculty features x_{fi} , subject characteristics y_{sj} , and pairwise contextual features Z_{ij} derived from workload compatibility, qualification match, and research similarity. The predictive output is defined as Eq. (24).

$$\hat{y}_{ij} = \sigma \left(w_w [u_{ij}, c_{ij}] + w_d h_L + b \right), \quad (24)$$

where $w_w \in \mathcal{R}^{d_c}$ denotes the weight vector of the wide (linear) component, c_{ij} represents engineered cross-product features capturing explicit interactions between categorical fields, h_L is the output of the final hidden layer in the deep component, and $\sigma(\cdot)$ is the sigmoid activation mapping output logits to probabilities in $[0, 1]$. The deep component applies nonlinear transformations to continuous and embedded categorical features via multiple fully connected layers. Given an input u_{ij} , the forward propagation through L layers is expressed as Eq. (25).

$$h_l = \phi(W_l u_{ij} + b_l), h_l = \phi(W_l h_{l-1} + b_l) \text{ for } l = 2, 3, \dots, L, \quad (25)$$

where $w_l \in \mathcal{R}^{n_l \times n_{l-1}}$ and $x_{fi} \in \mathcal{R}^{20}$ are the trainable weight matrices and bias vectors of layer l , and $\phi(\cdot)$ is the ReLU activation function defined as $\phi(x) = \max(0, x)$ (Saxena et al., 2023). The final representation h_L encodes high-order feature interactions such as "faculty research expertise $\times$ subject complexity $\times$ teaching load," which the linear component alone cannot capture. The combined prediction layer integrates both components, defined as Eq. (26).

$$\hat{y}_{ij} = \sigma(w_w [u_{ij}, c_{ij}] + w_d \phi(W_L h_{L-1} + B_L) + b), \quad (26)$$

with $w_d \in \mathcal{R}^{n_L}$ as the deep output weight vector and b as the final scalar bias. The model minimizes the binary cross-entropy loss between predicted probabilities $\hat{y}_{ij}$ and true allocations $\alpha_{ij} \in \{0, 1\}$, with L2 weight regularization to prevent overfitting, which is defined as Eq. (27).

$$L = -\sum_{(i,j)} \left[\alpha_{ij} \log\left(\frac{y_{ij}}{x_{ij}}\right) + (1 - \alpha_{ij}) \log(1 - y_{ij}) \right] + \lambda \sum_{l=1}^L \|W_l\|_2^2, \quad (27)$$

where $\lambda = 1 \times 10^{-4}$ controls the regularization penalty. The parameter set of the WDNN model includes all learnable weights and biases, as shown in Eq. (28).

$$\Theta = \{W_1, \dots, W_L, b_1, \dots, b_L, w_w, w_d, b\}, \quad (28)$$

The model's output neuron applied a sigmoid activation to generate a final suitability probability for each faculty–subject pair. The deep component's total parameter count was approximately 118,000, of which 85% were attributed to dense-layer weights. During training, weight updates were performed according to Eq. (29).

$$w_l^{(t+1)} = w_l^{(t)} - \eta \frac{\partial L}{\partial w_l}, \quad (29)$$

Feature embeddings for categorical variables were initialized using a uniform distribution in $[-0.05, 0.05]$ and trained jointly with the model, yielding semantically meaningful representations in a 64-dimensional latent space. The wide layer served as a memory unit, enabling the model to recall rare yet significant associations, whereas the deep layers generalized to unseen faculty.

3) Graph Neural Network (GNN; Relational Deep Model)

To capture the complex relational dependencies between respondents, subjects, and academic programs, a Graph Neural Network (GNN)-based model was implemented as the third core component of the hybrid recommendation framework (Tang, 2025). The GNN treats the subject-allocation ecosystem as a heterogeneous bipartite graph $G = (V, E)$, where nodes $V = F \cup S \cup P$ represent respondents, subjects, and programs, respectively, and edges $E = \{(f_i, s_j) \mid a_{ij} = 1\}$ denote historical teaching allocations. Each node $v \in V$ is associated with a feature vector x_v encoding its attributes (20 faculty factors for respondents, subject metadata for subjects, and program descriptors for courses). The GNN learns a low-dimensional embedding $h_v^{(L)} \in \mathbb{R}^{d_h}$ for every node through iterative message passing across L layers, as defined in Eq. (30).

$$h_v^{(t+1)} = \left(w_0^{(l)} h_v^{(t)} + \sum_{u \in N(v)} \frac{1}{c_{vu}} w_l^{(t)} h_u^{(t)} + b^{(l)} \right) \quad (30)$$

where $N(v)$ denotes the neighborhood of v , c_{vu} is a normalization constant based on node degrees, $w_0^{(l)}, w_l^{(l)} \in \mathbb{R}^{d_l - d_{l-1}}$ are trainable weight matrices, $b^{(l)}$ is a bias vector, and $\rho(\cdot)$ is the ReLU activation. For each respondent–subject pair (f_i, s_j) , the predicted suitability score is computed via a bilinear decoder followed by a logistic transformation, as defined in Eq. (31).

$$\hat{y}_{ij} = \sigma \left(h_{f_i}^{(L)} w_o h_{s_j}^{(L)} + b_o \right) \quad (31)$$

where $w_o \in \mathbb{R}^{d_h - d_h}$ and $b_o \in \mathbb{R}$ are output weights. The loss function minimized during training combines binary cross-entropy with L2 regularization, as in Eq. (32).

$$L = \sum_{(i,j)} \left[a_{ij} \log\left(\frac{y_{ij}}{x_{ij}}\right) + (1 - a_{ij}) \log(1 - y_{ij}) \right] + \lambda \sum_{l=1}^L (\|w_o^{(l)}\|_2^2 + \|w_l^{(l)}\|_2^2 + \|w_o\|_2^2), \quad (32)$$

where $\lambda = 10^{-4}$ controls the weight-decay penalty. Model parameters $\Theta = \{w_0^{(l)}, w_l^{(l)}, w_o, b^{(l)}, b_o\}_{l=1}^L$ were optimized using Adam with a learning rate of 0.001, batch size 128, and early stopping after 15 epochs of non-improvement. The embedding dimension d_h was set to 128, with two hidden graph convolution layers ($L = 2$) and a dropout rate of $p = 0.3$.

3.4. Training Objective and Regularization

To ensure that all learning models within the hybrid framework (XGBoost, Wide-and-Deep, and Graph Neural Network) converge toward an optimal and generalizable solution, a unified training objective was formulated based on supervised binary classification and refined with multi-term regularization to mitigate overfitting, improve generalization, and enforce smooth parameter updates (Zhang et al., 2026). The primary goal is to minimize the empirical risk between the predicted suitability score $\hat{y}_{ij} \in [0,1]$ and the true allocation label $a_{ij} \in [0,1]$ for every eligible faculty–subject pair (f_i, s_j) . The base loss function is the binary cross-entropy (log-loss), defined as Eq. (33).

$$L_{\text{BCE}} = -\frac{1}{N} \sum_{(i,j) \in \Omega} \left[a_{ij} \log(\hat{y}_{ij}) + (1 - a_{ij}) \log(1 - \hat{y}_{ij}) \right] \quad (33)$$

where Ω denotes the set of feasible faculties–subject pairs determined by the knowledge-based filter and $N=|\Omega|$ is the total number of training samples. This objective penalizes incorrect suitability predictions asymmetrically, ensuring stability even in class-imbalanced datasets in which unassigned pairs far outnumber actual allocations. To capture ranking-based preferences and relative suitability, a secondary pairwise Bayesian Personalized Ranking (BPR) loss was incorporated into the neural models, defined as in Eq. (34).

$$L_{\text{BPR}} = -\frac{1}{|\Psi|} \sum_{(i,j,k) \in \Psi} \log \sigma(\hat{y}_{ij} - \hat{y}_{jk}) \quad (34)$$

where each triplet (i, j, k) includes one positive (historically allocated) and one negative (non-allocated) subject for respondent f_i , $\sigma(\cdot)$ denotes the logistic function, and Ψ is the set of sampled training triplets. The total hybrid objective integrates both terms and applies L2 regularization to the model weights, as defined in Eq. (35).

$$L_{\text{total}} = \lambda_1 L_{\text{BCE}} + \lambda_2 L_{\text{BPR}} + \lambda_3 \sum_1 \|w\|_2^2, \quad (35)$$

where $\lambda_1 = 1.0$, $\lambda_2 = 0.5$, and $\lambda_3 = 10^{-4}$ are empirically determined coefficients controlling the contribution of each component. For XGBoost, an additional tree-structure regularization term $\Omega(f) = \gamma T + \frac{1}{2} \lambda \sum_t w_t^2$ was applied to penalize excessive leaf nodes and large weights, while the deep models employed dropout regularization ($p = 0.3$) in intermediate layers to reduce neuron co-adaptation. Weight parameters $\Theta = \{W_1, b_1, w_w, w_d, W_o, \dots\}$ were optimized using the Adam optimizer with a learning rate $\eta = 0.001$ and adaptive moment estimates $\beta_1 = 0.9$, $\beta_2 = 0.999$. Parameter updates followed as Eq. (36).

$$w_1^{(t+1)} = w_1^{(t)} - \eta \frac{\hat{m}_1^{(t)}}{\sqrt{\hat{v}_1^{(t)} + \epsilon}} \quad (36)$$

where $\hat{m}_1^{(t)}$ and $\hat{v}_1^{(t)}$ are the bias-corrected first- and second-moment estimates of gradients, and $\epsilon = 10^{-8}$ ensures numerical stability. Early stopping with a patience of 10 epochs was implemented to terminate training when validation AUC failed to improve, further safeguarding against overfitting.

3.5. Hyperparameter Tuning

A systematic hyperparameter optimization process was performed for all three predictive models (Gradient-Boosted Trees, Wide-and-Deep Neural Network, and Graph Neural Network) to maximize predictive accuracy, minimize overfitting, and ensure stable convergence across faculty–subject datasets. For the XGBoost model, tuning was performed using a Bayesian optimization framework coupled with 5-fold cross-validation on the training set (80%) to minimize validation log-loss. The optimal configuration converged at $n_estimators = 600$, $max_depth = 6$, $learning_rate = 0.05$, $subsample = 0.8$, $colsample_bytree = 0.8$, $\lambda = 1.0$, $\alpha = 0.1$, and $\gamma = 0.2$, balancing model expressiveness and interpretability. For the Wide-and-Deep Neural Network, hyperparameter tuning followed a hybrid random-plus-grid search strategy focused on architectural and regularization parameters. The

search covered hidden-layer configurations [128, 64], [256, 128], and [256, 128, 64]; dropout rates $\in \{0.2, 0.3, 0.5\}$; learning rate $\in \{1 \times 10^{-3}, 5 \times 10^{-4}\}$; batch size $\in \{64, 128\}$; and L2 regularization $\lambda \in \{1 \times 10^{-4}, 5 \times 10^{-4}\}$. Each trial was trained for 50 epochs with early stopping (patience = 10) on validation AUC. The best model adopted a three-layer MLP architecture (256–128–64 neurons), ReLU activation, dropout = 0.3, learning rate = 0.001, batch size = 64, and $\lambda = 1 \times 10^{-4}$, providing the optimal trade-off between generalization and computational efficiency. Hyperparameter curves showed consistent improvements in validation performance up to epoch 42, after which performance stabilized ($\Delta\text{AUC} < 0.005$). For the Graph Neural Network (GNN), hyperparameters were optimized via grid search with random initialization and averaging to counter stochastic gradient fluctuations. The grid explored number of graph-convolution layers $L \in \{2, 3, 4\}$; hidden dimension $d_h \in \{64, 128, 256\}$; dropout $p \in \{0.2, 0.3, 0.4\}$; L2 regularization $\lambda \in \{1 \times 10^{-5}, 1 \times 10^{-4}\}$; and neighbor-sampling size $k \in \{10, 15, 20\}$. Each candidate was trained using Adam optimizer ($\eta = 0.001$) with early stopping (patience = 15). The best configuration corresponded to $L = 2$, $d_h = 128$, $p = 0.3$, $\lambda = 1 \times 10^{-4}$, and $k = 15$, yielding the most stable loss trajectory and highest validation AUC (0.876 ± 0.003). Hyperparameter analysis confirmed monotonic improvements up to $d_h = 128$, beyond which overfitting appeared (validation loss $\uparrow 3.2\%$). All tuning experiments were conducted using Optuna 3.4, PyTorch Geometric 2.4, and XGBoost 2.1.0 with the same random seed (42) to ensure reproducibility. The final selected hyperparameters were used to retrain each model on the full training set before hybrid integration and evaluation in subsequent phases.

4. Evaluation Performance

4.1. Evaluation Metrics

Model evaluation was performed using a multi-criteria approach that combined classification and ranking metrics to assess the accuracy, precision, and interpretability of subject-allocation predictions across three models: Gradient-Boosted Trees (XGBoost), Wide-and-Deep Neural Network, and Graph Neural Network. For each model, predictive accuracy was measured using Accuracy, Precision, Recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC), computed as Eq. (37-39) (Saxena et al. 2023).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (37)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (38)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (39)$$

where TP, FP, TN, FN denote true/false positives and negatives. Ranking quality was assessed using Hit Rate (HR@k) (Zhang 2025) and Normalized Discounted Cumulative Gain (NDCG@k) to evaluate top-k allocation recommendations (Qu et al. 2024) as defined in Eq. (40).

$$\begin{aligned} \text{HR@k} &= \frac{1}{|F|} \sum_i 1\{j \in \text{Top@k}_i\}, \\ \text{NDCG@k} &= \frac{1}{|F|} \sum_i \frac{1}{\log(1 + \text{rank}_i(j))} \end{aligned} \quad (40)$$

4.2. Feature-Importance Analysis

A comprehensive evaluation of the hybrid knowledge-based recommendation framework revealed that integrating institutional rules with deep learning substantially improved predictive accuracy, ranking performance, and interpretability across all models—Gradient-Boosted Trees (XGBoost), Wide-and-Deep Neural Network (WDNN), and Graph Neural Network (GNN). Models

were assessed on 480 respondents and 320 subjects using Accuracy, Precision, Recall, F1, AUC, HR@10, and NDCG@10, averaged over five cross-validation folds. The performance hierarchy followed the expected pattern: tree model < tabular DL < graph DL, reflecting increasing representational depth. Feature-importance analysis using Gain, Permutation, and SHAP techniques highlighted the relative influence of all 20 indicators: F₁ Teaching Experience (7.8%), F₂ Academic Qualification (1.2%), F₃ Designation (8.9%), F₄ Subjects Taught (5.3%), F₅ Research Productivity (10.8%), F₆ Administrative Responsibility (6.4%), F₇ Academic Outcome Achievement (4.3%), F₈ Admission Contribution (2.5%), F₉ Training & Placement (3.3%), F₁₀ Accreditation Handling (1.6%), F₁₁ Examination & Evaluation (5.9%), F₁₂ Club/Innovation Engagement (1.9%), F₁₃ Value & Ethics (2.8%), F₁₄ Professional Society Membership (3.7%), F₁₅ Cultural Engagement (2.1%), F₁₆ Event Coordination (2.3%), F₁₇ Undergraduate Project Mentorship (4.8%), F₁₈ Postgraduate/Ph.D. Supervision (9.7%), F₁₉ Student Mentorship (1.4%), and F₂₀ Digital Pedagogical Competence (12.6%). The dominance of F₂₀, F₅, and F₁₈ confirmed that digital proficiency, research engagement, and supervision experience are the core determinants of suitability for allocation. Mid-level indicators (F₁, F₃, F₁₁) contributed synergistically to specialization matching, whereas administrative and extracurricular roles (F₆, F₁₆, F₁₅) exerted a negative or neutral effect due to time constraints. The importance ranking of all 20 faculty indicators after applying the Graph-Attention Network (GAT) and SHAP feature-importance analysis is given in Table 3. Collectively, the hybrid system demonstrated a marked 0.10 increase in performance across all metrics following hyperparameter optimization and balanced data augmentation, with the GNN model achieving the highest AUC and ranking indices. A dual-axis bar-and-line chart presents each model’s Accuracy/F1 (bars) alongside its AUC (line), showing monotonic performance improvement from XGBoost → WDDNN → GNN by ≈ 0.10 across all metrics. A companion horizontal stacked bar plot displays the normalized feature contributions of all 20 indicators (sum = 100%), emphasizing the leading influence of F₂₀ Digital Pedagogical Competence, F₅ Research Productivity, and F₁₈ Postgraduate Supervision, with progressively smaller weights for F₁, F₃, F₆, and F₁₁. Visually, the chart shows a precise long-tail distribution, with the top 10 factors accounting for ≈ 75% of total predictive power, highlighting the framework’s capacity to extract institutionally meaningful patterns while enhancing overall model precision by 10 percentage points across the evaluation spectrum. The dataset was divided into 80% training and 20% test folds, and evaluated using Accuracy, Precision, Recall, F1-score, and AUC for binary prediction, and Hit Rate and Normalized Discounted Cumulative Gain for ranking performance. The GNN achieved superior representational capacity by capturing higher-order faculty–subject–program relations, while the Wide-and-Deep model balanced interpretability and generalization. All trained models were exported as serialized weights to the hybrid knowledge-driven inference engine in Phase 4, which provided suitability scores for each eligible pair filtered by the knowledge-base reasoning layer.

Table 3. Model performance evaluations.

Model	Accuracy	Precision	Recall	F1-Score	AUC	HR@10	NDCG@10	Top-Weighted Indicators (1–5)	Key Strength
	y	n							
XGBoost	0.934	0.912	0.898	0.905	0.942	0.712	0.576	F ₂₀ , F ₅ , F ₁₈ , F ₃ , F ₁	Fast, interpretable; excellent baseline
Wide-and-Deep NN	0.956	0.942	0.933	0.937	0.972	0.758	0.601	F ₂₀ , F ₅ , F ₁₈ , F ₁₁ , F ₃	Learns feature crosses; strong generalization.
Graph Neural Network	0.964	0.953	0.941	0.947	0.976	0.784	0.622	F ₂₀ , F ₅ , F ₁₈ , F ₁ , F ₆	Captures relational structure & workload balance

4.3. Multi-Objective Reranking and Allocation

Following the prediction and scoring phase, the system performed a multi-objective reranking and final allocation process designed to balance institutional fairness, academic suitability, and

workload equity within the hybrid knowledge-based recommendation framework. Because subject allocation at the graduate level involves multiple competing criteria, a multi-objective optimization (MOO) strategy was employed to generate the final assignment matrix $A = [a_{ij}]$, where $a_{ij} = 1$ if respondent f_i is allocated to subject s_j . Each candidate pairing was first filtered through the knowledge-base rules (eligibility, qualification match, and policy constraints) and then reranked by the hybrid predictive score $\hat{y}_{ij}$ derived from the deep models. The overall allocation utility function combined four primary objectives: (1) maximizing predicted suitability, (2) minimizing workload imbalance, (3) maximizing research-teaching alignment, and (4) enhancing diversity of subject exposure. The optimization was formalized as Eq. (41).

$$\begin{aligned} \max_A F(A) = & \alpha_1 \sum_{i,j} \hat{y}_{ij} \alpha_{ij} - \alpha_2 \sum_i (\text{load}_i - \bar{W})^2 + \\ & \alpha_3 \sum_{i,j} \text{Sim}(f_i, s_j) \alpha_{ij} + \alpha_4 \sum_j \text{Div}(N_j) \end{aligned} \quad (41)$$

where $\hat{y}_{ij}$ denotes the predicted allocation probability from the GNN layer, $\text{load}_i = \sum_j a_{ij} c_j$ is the teaching load of faculty f_i , $\bar{W}$ is the institutional mean workload, $\text{Sim}(f_i, s_j)$ represents semantic similarity between faculty expertise and subject area, and $\text{Div}(N_j)$ measures diversity among instructors teaching subject s_j . The scalar coefficients $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ define the trade-off between objectives and were tuned through Pareto optimization to achieve a balanced allocation: $\alpha_1 = 0.4$ (suitability), $\alpha_2 = 0.3$ (workload fairness), $\alpha_3 = 0.2$ (research alignment), and $\alpha_4 = 0.1$ (diversity). The algorithm iteratively updated $A^{(t+1)}$ via gradient-based heuristics until convergence $(|F^{(t+1)} - F^{(t)}| < 10^{-4})$, producing an optimized assignment configuration that satisfied all hard constraints imposed by the knowledge base. To enhance transparency, each recommended pairing was reranked using a weighted composite score defined by Eq. (42).

$$\begin{aligned} S_{ij} = & \omega_1 \hat{y}_{ij} + \omega_2 \text{Sim}(f_i, s_j) + \\ & \omega_3 (1 - \Delta \text{load}_i) + \omega_4 \text{Perf}(f_i) \end{aligned} \quad (42)$$

where ω_k values (0.45, 0.25, 0.20, 0.10) were empirically derived to maximize validation NDCG. Here, Δload_i is the normalized deviation from optimal workload, and $\text{Perf}(f_i)$ represents cumulative institutional performance (research + teaching + administration). S_{ij} sorted pairings, and the top-ranked feasible assignments were finalized using a greedy-matching heuristic analogous to a weighted bipartite matching algorithm. Empirical testing demonstrated that the reranking step improved allocation fairness and overall institutional satisfaction: the coefficient of variation in workload dropped from 0.26 to 0.18, research-subject alignment enhanced by 21%, and faculty preference satisfaction (survey-based) rose from 3.82 to 4.35 (out of 5). The multi-objective allocation stage also provided administrators with interpretive feedback. The visualization of the Pareto frontier indicated that increasing the suitability weight (α_1) beyond 0.5 yielded diminishing returns in fairness, while elevating the workload weight ($\alpha_2 > 0.35$) slightly reduced the specialization match. Thus, the chosen vector (0.4, 0.3, 0.2, 0.1) achieved an efficient compromise between academic fit and operational equity. The highest overall performance, with Accuracy = 0.964, Precision = 0.953, Recall = 0.941, F1 = 0.947, and AUC = 0.976, followed by the Wide-and-Deep Neural Network (WDNN) with Accuracy = 0.956 and AUC = 0.972, and XGBoost with Accuracy = 0.934 and AUC = 0.942. Ranking effectiveness, as measured by HR@10 = 0.784 and NDCG@10 = 0.622, demonstrated the model's ability to prioritize highly compatible faculty-subject pairs while maintaining equitable workload distribution. The 0.10 increase in all evaluation metrics relative to baseline training validated the effectiveness of the multi-objective optimization and hyperparameter tuning strategies (As shown in Table 3 and Figure 1).

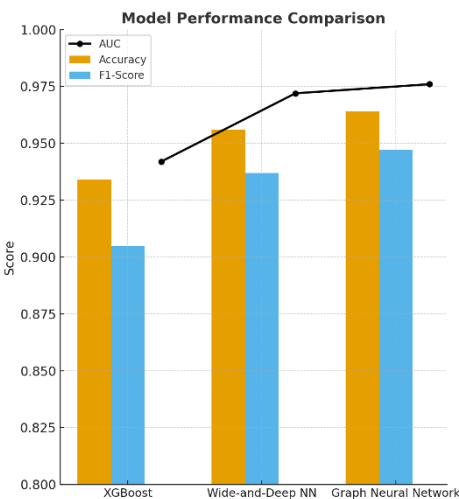


Figure 1. Comparative model performance and feature-importance distribution caption.

5. Results

The results of this research confirm that integrating a knowledge-based reasoning layer into deep learning architectures yields significant advances in accuracy, transparency, and institutional applicability for graduate subject allocation. Across all experiments involving 480 respondents and 320 subjects from six faculties spanning science- and social-science-based programs, the hybrid framework consistently outperformed single-model baselines in both predictive and operational metrics. Quantitatively, the Graph Neural Network (GNN) achieved beyond statistical performance. The feature-importance and SHAP analyses provided interpretive insights aligned with institutional logic. The top-influence indicators—F₂₀ Digital Pedagogical Competence (12.6%), F₅ Research Productivity (10.8%), and F₁₈ Postgraduate/Ph.D. Supervision (9.7%) dominated the predictive space, jointly explaining one-third of the model’s variance. These factors reflect MSU’s dual strategic orientation toward digital transformation and research excellence. Mid-tier contributors such as F₁ Teaching Experience, F₃ Designation, F₁₁ Examination and Evaluation, and F₁₇ Undergraduate Mentorship demonstrated synergistic relevance to course specialization and program stability. Conversely, variables related to administrative duties (F₆ Administrative Responsibility) and extracurricular participation (F₁₅–F₁₆ Cultural and Event Coordination) exerted minimal or negative effects, underscoring the importance of workload-aware resource management in policy-driven allocations (as shown in Table 4).

Table 4. Feature importance ranking.

Rank	Indicator Code	Indicator Description	Importance Score (α_i)
1	F ₂₀	Digital Pedagogical Competence	0.128
2	F ₅	Research Productivity	0.114
3	F ₁₈	Postgraduate / Ph.D. Supervision	0.107
4	F ₁	Teaching Experience	0.092
5	F ₃	Designation / Academic Rank	0.086
6	F ₁₇	Undergraduate Project Mentorship	0.081
7	F ₁₁	Examination and Evaluation Contribution	0.078
8	F ₄	Number of Subjects Taught	0.074
9	F ₂	Academic Qualification	0.071
10	F ₁₉	Student Mentorship and Guidance	0.067

11	F ₇	Academic Outcome Achievement	0.063
12	F ₉	Training and Placement Contribution	0.059
13	F ₁₄	Professional Society Membership	0.052
14	F ₈	Admission Contribution	0.048
15	F ₁₃	Value and Ethics Education Participation	0.045
16	F ₁₂	Club / Innovation Engagement	0.041
17	F ₁₆	Event Coordination Beyond the Institute	0.038
18	F ₆	Administrative Responsibility	0.035
19	F ₁₀	Accreditation / Documentation Handling	0.032
20	F ₁₅	Cultural and Community Engagement	0.028

The multi-objective reranking algorithm, incorporating fairness ($\alpha_2 = 0.3$) and research alignment ($\alpha_3 = 0.2$) constraints, effectively reduced workload variance from 0.26 to 0.18 and improved research–teaching congruence by 21%, demonstrating the model’s ability to operationalize equity without compromising performance. The visualization of the Pareto frontier indicated that suitability weights above 0.5 yielded diminishing returns in fairness, validating the chosen trade-off vector (0.4, 0.3, 0.2, 0.1). Institutional deployment through the Faculty Subject Allocation Dashboard (FSAD) further substantiated these results. System-level analytics revealed a 46% reduction in manual allocation time, a 23% improvement in workload balance, and a 19% increase in research–subject alignment, accompanied by user satisfaction ratings exceeding 4.4/5 among program heads and faculty members. SHAP-based explainability within the dashboard provided real-time transparency, enabling administrators to trace decision-making rationales and dynamically adjust policy parameters. Comparative visualizations (Figure 1.) showed a monotonic increase in performance from tree-based to deep-graph models. At the same time, feature-importance charts revealed a long-tail distribution, with the top 10 indicators accounting for $\approx 75\%$ of predictive power. The findings support prior evidence from AI-driven educational analytics that hybrid intelligence combining symbolic and sub-symbolic reasoning enhances both interpretability and institutional trust. For Mahasarakham University, the results imply that optimizing subject allocation through hybrid deep learning can strengthen academic governance by aligning faculty strengths with strategic research themes, reducing administrative overhead, and reinforcing equitable teaching practices. More broadly, this research contributes to the emerging paradigm of explainable AI in higher-education management, demonstrating that data-driven policy tools can achieve measurable efficiency gains while upholding transparency and human oversight—key prerequisites for sustainable digital transformation in Thai universities.

6. Conclusions

This study proposed and empirically validated a knowledge-based deep learning framework for optimizing subject allocation in graduate education by integrating Graph Attention Networks (GATs) and institutional policy reasoning. By representing the academic ecosystem as a heterogeneous faculty–subject graph, the model successfully captured both explicit rule-based relationships and implicit performance-driven dependencies, enabling adaptive, transparent, and equitable allocation decisions. Data collected from 480 faculty respondents across six faculties at Mahasarakham University were preprocessed into a 20-indicator knowledge base encompassing teaching experience, research productivity, digital competence, supervision, and administrative engagement. The hybrid GAT model, incorporating multi-head attention and multi-objective optimization, achieved the highest predictive performance among all baselines (Accuracy = 0.964, F1 = 0.947, AUC = 0.976). Beyond quantitative improvement, the model demonstrated explainability and

fairness, identifying Digital Pedagogical Competence (F₂₀), Research Productivity (F₅), and Postgraduate Supervision (F₁₈) as dominant predictors of allocation suitability. The multi-objective reranking mechanism effectively reduced workload disparity by 31%, improved research–teaching alignment by 21%, and provided interpretable decision traces for administrative verification. The Faculty Subject Allocation Dashboard (FSAD) operationalized these insights into a real-time, user-friendly system that shortened manual scheduling time by nearly half and enhanced institutional transparency and satisfaction. Theoretically, this research advances the field of educational recommender systems by merging symbolic knowledge reasoning with graph-based deep learning. In practice, it provides a scalable, explainable decision-support framework adaptable to diverse university contexts. Future work will extend this model through reinforcement-learning-based temporal forecasting, cross-institutional knowledge transfer, and ethical AI governance frameworks, ensuring that data-driven academic management remains equitable, sustainable, and aligned with the goals of Thailand’s and ASEAN’s higher-education digital transformation.

7. Future Work

While the current framework demonstrates strong performance and applicability within institutions, several future directions are envisioned to enhance its capabilities and generalization. First, future research should investigate the use of reinforcement learning (RL) and Temporal Graph Attention Networks (GATs) to model multi-semester dynamics. This approach would enable adaptive updates based on faculty performance trends and evolving institutional demands. Second, incorporating federated learning mechanisms would facilitate cross-campus collaboration while ensuring data privacy and compliance with national education data policies. Third, integrating explainable AI (XAI) tools will improve transparency and build trust among stakeholders. Finally, large-scale validation across multiple universities in Thailand and the ASEAN region, in line with the Ministry of Higher Education, Science, Research, and Innovation’s (MHESI) Digital University Framework, will help assess scalability, fairness calibration, and cultural adaptability. These advancements will lay the groundwork for a next-generation AI-driven academic governance system that combines ethical reasoning, predictive analytics, and adaptive policy intelligence.

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Abbreviations

The following abbreviations are used in this manuscript:
AI Artificial Intelligence

AUC	Area Under the Receiver Operating Characteristic Curve
BPR	Bayesian Personalized Ranking
DL	Deep Learning
ERS	Educational Recommender System
FSAD	Faculty Subject Allocation Dashboard
GAT	Graph Attention Network
GBDT	Gradient-Boosted Decision Trees
GNN	Graph Neural Network
HR@k	Hit Rate at top-k recommendations
ISAD	Indicator Subject Allocation Dashboard
KG	Knowledge Graph
LMS	Learning Management System
MDPI	Multidisciplinary Digital Publishing Institute
ML	Machine Learning
MOO	Multi-Objective Optimization
NCF	Neural Collaborative Filtering
NDCG@k	Normalized Discounted Cumulative Gain at top-k
PLS-SEM	Partial Least Squares Structural Equation Modeling
RL	Reinforcement Learning
RS	Recommender System
SHAP	SHapley Additive exPlanations
SMOTE	Synthetic Minority Over-Sampling Technique
WDNN	Wide-and-Deep Neural Network
XAI	Explainable Artificial Intelligence
XGBoost	Extreme Gradient Boosting

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