

Leveraging AI for Higher Education Human Resources: A Systematic Literature Review

Maria Veronica^{1,4*}, Wendi Usino², Arief Wibowo³

^{1,2,3} Computer Science Study Program, Faculty of Information Technology, Universitas Budi
Luhur, Indonesia

⁴ Informatic System Study Program, Institut Teknologi dan Bisnis PalComTech, Indonesia

ABSTRACT

The integration of Artificial Intelligence (AI) in Human Resource Development (HRD) policies for academic staff in Higher Education Institutions (HEIs) is often constrained by the misalignment between computational capabilities and institutional governance. While HEIs generate substantial datasets through the Tri Dharma (the three pillars of higher education: teaching, research, and community service), this data remains underutilized for proactive policy-making. To map the state-of-the-art and identify existing research gaps, this study conducts a Systematic Literature Review (SLR) and bibliometric analysis of 400 unique peer-reviewed documents, obtained from an initial 485 records retrieved from Scopus (n = 260) and Web of Science (n = 225) after removing 85 duplicates, covering the seven-year period from 2018 to 2024. Visual analysis using VOSviewer reveals a distinct semantic-policy discrepancy, showing that semantic technologies and predictive AI models are researched as isolated technical domains, seldom integrated into comprehensive institutional governance. To bridge this gap, this paper proposes a framework for Higher Education Human Resources for Lecturer Career Development. The proposed framework integrates machine learning classifiers (Naïve Bayes, K-Means, and Apriori association) with a semantic Knowledge Graph layer to transform descriptive academic metrics into explainable, policy-conforming recommendations. Preliminary expert consultation with LLDIKTI Region II highlights the conceptual viability of the Framework for Higher Education Human Resources for Lecturer Career Development in mitigating administrative bottlenecks, supporting objective career path design, and minimizing human subjectivity in lecturer performance evaluations.

Keywords: *Artificial Intelligence; Knowledge Graph; Policy Recommendation; Higher Education; Human Resource Development; Systematic Literature Review.*

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***Correspondence Address:**

2411700061@student.budiluhur.ac.id

1. INTRODUCTION

Higher Education Institutions (HEIs) are currently required to continuously develop and transform, particularly in the application of digital technology. Moving towards the Education 4.0 model, academic human resource management constitutes an essential strategic pillar [1, 2]. In Indonesia, lecturers, as primary academic drivers, are comprehensively assessed across mandatory statutory contributions known as the Tri Dharma of Higher Education, encompassing Teaching, Research, and Community Service [3, 4]. However, faculty HR policy management, particularly concerning the acceleration of academic careers and functional promotions (*Jabatan Fungsional Dosen*), is frequently fraught with procedural delays, fragmented evaluations, and evaluative subjectivity, resulting in systemic career stagnation [5]. Institutional governance commonly relies upon manual tracking and periodic retrospective appraisals that fail to capture the non-linear, dynamic developmental trajectories of academic staff, leaving administrative policies predominantly reactive [6].

To overcome these reactive limitations, academic institutions are increasingly exploring the integration of Artificial Intelligence (AI), machine learning, and data mining [7]. AI-driven policy recommendation systems offer transformative potential by analyzing heterogeneous faculty datasets—spanning teaching workloads, research publication indexes, grant acquisitions, and community service milestones—to generate proactive institutional strategies [8]. Machine learning classifiers can potentially mitigate human subjectivity in performance appraisals [9]. However, scholars increasingly caution against the substantial risks of algorithmic bias within HR systems [5]. If machine learning algorithms are trained on historical institutional datasets, they risk learning, magnifying, and perpetuating historical inequities, such as

gender imbalances in research allocations, departmental evaluation discrepancies, and career velocity gaps [5, 12, 33]. Furthermore, conventional black-box deep learning models lack interpretability, generating an acute trust deficit among academic staff who require transparent, regulatory-compliant reasoning behind career advancement recommendations [16, 34]. Consequently, AI frameworks in higher education must be designed not as autonomous decision-makers, but as explainable Decision Support Systems (DSS) that harmonize computational analytics with human judgment, ethical governance, and statutory regulations [5, 15, 16, 35].

A major structural bottleneck in existing AI-based HR models is the pervasive semantic gap. While advanced predictive algorithms (such as Decision Trees, Support Vector Machines, and Neural Networks) achieve high statistical accuracy in forecasting faculty performance trends [10, 14], they cannot explain the underlying causal mechanisms or interdependencies among Tri Dharma variables [15]. Traditional tabular data mining treats faculty accomplishments as isolated relational entries rather than deeply contextualized academic pathways [16]. Because university administrators require explainable, evidence-based reasoning to make consequential personnel decisions, purely descriptive or black-box statistical metrics prove insufficient [16].

To address this semantic deficit, Knowledge Graphs (KGs) provide an expressive semantic architecture that connects disparate entities, accomplishments, and statutory policies in ways relational databases cannot [17]. A Knowledge Graph can dynamically contextualize faculty research areas, identify collaborative interdisciplinary networks, and map individual records against complex national promotion criteria [17]. To systematically diagnose the current global state of the art and delineate the precise intellectual boundaries where AI, Knowledge Graphs, and

Higher Education HR intersect, this study conducts a Systematic Literature Review and quantitative bibliometric mapping using VOSviewer [12, 13]. To systematically structure the review and guide the subsequent Framework design, this research is anchored around three formal Research Questions:

RQ1: What is the current state-of-the-art and thematic clustering of scientific literature concerning the application of AI within higher education human resource governance?

RQ2: Where are the primary semantic and structural gaps between current machine learning prediction algorithms and the implementation of academic career policy frameworks?

RQ3: How can a conceptual framework combining machine learning and Knowledge Graphs (Framework for Higher Education Human Resources for Lecturer Career Development) be structured to bridge the gap between quantitative academic metrics and explainable policy recommendations?

2. METHODS

This research applies bibliometric research and a Systematic Literature Review (SLR) to elaborate the intellectual framework and research limitations in topics related to AI-based policy recommendation for Human Resource Development in Higher Education Institutions (HEIs). To ensure transparency, reproducibility, and methodological rigor, the research design adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines [11] combined with quantitative bibliometric mapping and network visualization using VOSviewer [12, 13].

2.1 Data Exploration

In order to make the dataset complete and representative, metadata was extracted from

global and reputable scientific databases, specifically Scopus and Web of Science (WoS) Core Collection on October 15, 2024 [9, 10]. Utilizing multiple major scientific portals mitigates database selection bias and provides an exhaustive overview of the scientific landscape. The search was strictly restricted to peer-reviewed documents published in the English language [10] across the seven-year period from 2018 through 2024 [3, 10]. The Boolean search query applied across Title, Abstract, and Keywords was structured as follows:

TITLE-ABS-KEY (("Artificial Intelligence" OR "AI") AND ("Higher Education" OR "University") AND ("Human Resource Development" OR "HRD") AND ("Policy Recommendation" OR "Decision Support System"))

The primary identification stage yielded a total of 485 records (260 documents from Scopus and 225 documents from Web of Science). Following duplicate identification, exactly 85 duplicate records were systematically eliminated. To minimize subjective selection bias, the screening protocol was executed independently by two researchers, with consensus reached through structured discussion and consultation with a senior research advisor. All 400 unique articles satisfied full eligibility criteria and proceeded to the synthesis stage. The study selection process structured under the PRISMA 2020 statement is illustrated in Figure 1.

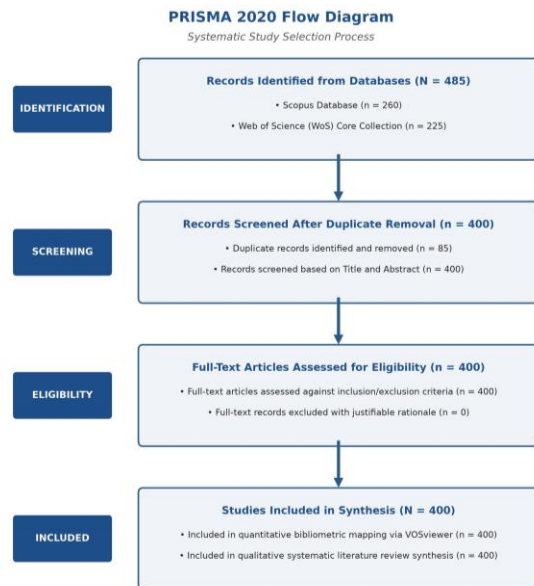


Figure 1. PRISMA 2020 flow diagram of the study selection process

Source: Processed by the author

2.2 Pre-processing Data

The retrieved bibliographic records were compiled in Mendeley and exported in Research Information Systems (RIS) format. The screening and eligibility assessment was strictly governed by concrete inclusion and exclusion criteria to ensure academic rigor. Non-empirical documents such as book reviews, editorial notes, master's theses, and dissertations were excluded, as were unrelated clinical AI studies (e.g., medical diagnostics). The operational inclusion and exclusion criteria are tabulated in Table 1.

Table 1. Inclusion and exclusion criteria

Criterion	Inclusion Criteria	Exclusion Criteria
Time Period	Published between January 1, 2018, and December 31, 2024 (7-year period) [3, 10].	Published before 2018 [10].
Language	Written exclusively in the English language [10].	Documents written in any non-English language [10].
Document Type	Peer-reviewed journal articles and full conference proceedings [11].	Book reviews, doctoral dissertations, master's theses, editorials, and errata [11].

Criterion	Inclusion Criteria	Exclusion Criteria
Focus Area	Studies addressing AI, machine learning, data mining, or knowledge graphs applied to faculty career paths, performance evaluation, or HEI HR policies [11].	General clinical/biomedical AI (e.g., medical diagnostics, glaucoma) [32], or pure algorithmic derivations lacking educational or HR applicability [11].

2.3 Mapping and Visualizing Bibliometrics

We used VOSviewer (version 1.6.20) to construct the bibliometric network by importing the cleaned dataset of 400 unique studies. This research employs two principal analytical methodologies: co-occurrence analysis and thematic clustering [12]. The co-occurrence analysis was conducted on All Keywords (combining author keywords and index keywords) to delineate the conceptual framework of the domain. To ensure technical reproducibility, the fractional counting method was selected to maintain network neutrality, guaranteeing that publications with long co-authorship rosters do not disproportionately distort thematic weighting [12]. The minimum keyword occurrence threshold was fixed at 5, pruning isolated terms while preserving a robust core network. Normalization was executed via the Association strength method [12], coupled with modularity-based clustering.

3. RESULTS AND DISCUSSION

The bibliometric analysis executed in VOSviewer reveals that scientific research related to AI-based policy recommendation systems, AI for human resource development, and AI in higher education exhibits structured thematic grouping. Metadata extracted from Scopus and Web of Science generated the keyword co-occurrence network depicted in Figure 2. The node size signifies term frequency, and the topological distance between nodes indicates thematic correlation.

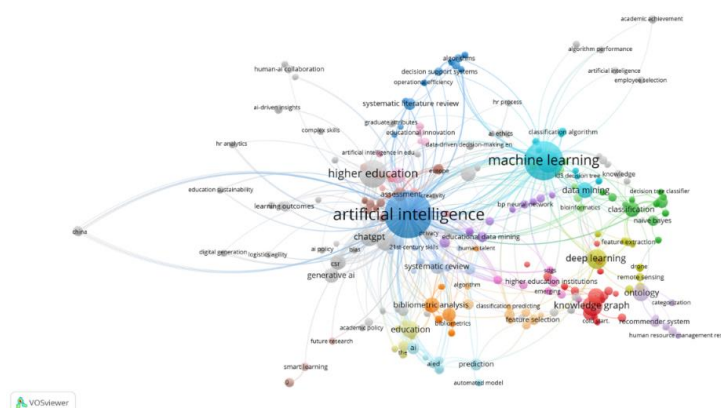


Figure 2. Bibliometric analysis network visualization

Source: Processed by the author

Table 2. Quantitative keyword cluster distribution and thematic literature gaps

Cluster	Identified Color	Keyword Count	Core Representative Keywords	Thematic Focus & Literature Gaps
Cluster 1	Blue	112	Artificial Intelligence, Higher Education, Education 4.0, Decision Support Systems [14]	Macro-level institutional transformations, university policy-making, and strategic challenges of AI adoption [4, 7, 12].
Cluster 2	Cyan	94	Machine Learning, Data Mining, Classification, Decision Tree, ID3, Prediction [14]	Highly technical predictive modeling, lecturer evaluation, and predictive analytics of academic performance [10, 11, 15].
Cluster 3	Purple / Pink	82	Talent Management, Human Resource Skills, Systematic Review, Faculty Development [15]	Conventional human resource development, faculty competency mapping, and professional career pathways [6, 9].
Cluster 4	Red	74	Knowledge Graph, Ontology, Recommendation System, Semantic Web [15]	Semantic data modeling, conceptual representation of institutional rules, and graph-based recommendation architectures [17, 30].
Cluster 5	Grey	38	Generative AI, LLMs, Academic Integrity, Policy [16]	Immediate impacts of generative AI tools and emerging governance guidelines surrounding academic policy [16].

The quantitative and topological results reveal five primary clusters within the network. Cluster 1 (Blue, 112 keywords) consists of major nodes in Artificial Intelligence and Higher Education, serving as the central bridge connecting technical innovation to educational governance. Cluster 2 (Cyan, 94 keywords) is dominated by technical machine learning and data mining nomenclature, such as classification algorithms, Decision Tree, and ID3, demonstrating that existing research heavily prioritizes statistical performance prediction.

Cluster 3 (Purple and Pink, 82 keywords) attractively connects administrative human resource skills, talent management, educational data mining, and systematic review, confirming

an emerging connection between data analytics and faculty development.

Cluster 4 (Red, 74 keywords) contains Knowledge Graph, ontology, and recommendation system terminology. Positioned in the central distribution, this cluster shows that while semantic technologies are maturing, they have not yet been utilized for policy recommendations in higher education. Cluster 5 (Grey, 38 keywords) near the center captures Generative AI and Large Language Models, representing emerging institutional policy adaptations.

4. DISCUSSION

The bibliometric visualization serves as a rigorous diagnostic of research across AI in

higher education governance. Topological distance analysis reveals a pronounced gap in policy topics related to machine learning and human resource development. The visualization of density, closeness, and clustering from the 400 selected research papers indicates that while predictive machine learning models and semantic knowledge graphs are robustly researched in isolation, they are disconnected from higher education HR policies. Concurrently, field observations through LLDIKTI Region II indicate persistent challenges in lecturer career progression. Institutions urgently require an integrated framework that leverages AI while maintaining regulatory alignment and human oversight, transitioning from reactive monitoring to proactive prescriptive guidance.

Analytical Integration of the Semantic-Policy Discrepancy

Structural visualization in VOSviewer demonstrates a clear separation between technical AI development and practical institutional implementation. While predictive analytics (Cluster 2) is widely explored, it operates primarily as an isolated statistical classification tool without integrating academic policy semantics. Current AI usage in higher education remains predominantly confined to monitoring dashboards rather than contextualizing individual lecturer career

trajectories. The Knowledge Graph (Cluster 4) offers the precise semantic capability required to encode non-linear relationships across Tri Dharma accomplishments and statutory promotion requirements (such as Indonesian PO PAK regulations). Connecting these disparate clusters provides the direct empirical justification for proposing an integrated framework.

The Empirical Basis and the Origin of the Framework for Higher Education Human Resources for Lecturer Career Development

Academic faculty frequently confront administrative bottlenecks, fragmented assessments, and prolonged evaluation cycles that lead to career stagnation. Current institutional frameworks provide descriptive tallies without offering actionable pathways for advancement. To bridge the gap identified in the bibliometric review, this study proposes the Framework for Higher Education Human Resources for Lecturer Career Development as a conceptual framework. As illustrated in Figure 3, Framework for Higher Education Human Resources for Lecturer Career Development synthesizes multi-tier machine learning analytics with a semantic Knowledge Graph layer to transform descriptive academic data into proactive, regulatory-conforming career policies.

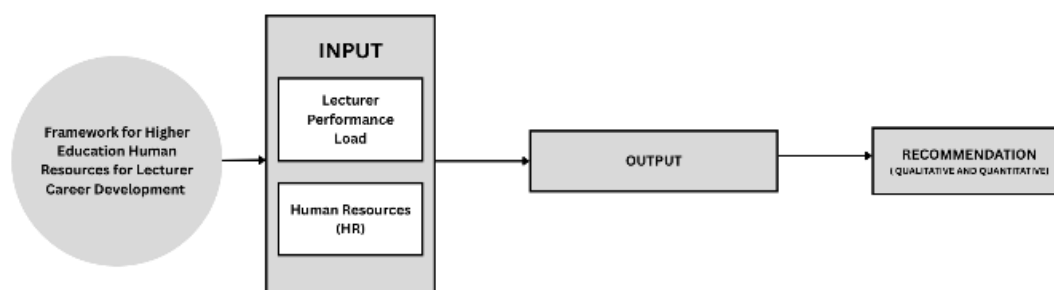


Figure 3. Framework for Higher Education Human Resources for Lecturer Career Development

Source: Processed by the author

The Framework for Higher Education Human Resources for Lecturer Career Development Framework consists of cohesive

layers that transform raw faculty metrics into strategic policy recommendations:

1. Data Ingestion Layer: Aggregates performance metrics across the Tri Dharma (teaching credit hours, research publications, and community service projects) from official higher education databases (PDDikti, SINTA, Lecturer Performance Load).
2. Intelligence Layer: Employs a hybrid computational suite with explicit theoretical justifications:
 - a. Bayes Classifier: Selected for its computational efficiency and probabilistic robustness in evaluating categorical, high-dimensional academic metrics (functional ranks, degree qualifications, and statutory KUM thresholds). Because promotion rubrics are governed by conditional compliance probabilities, Naïve Bayes accurately estimates the probability of promotion readiness.
 - b. K-Means Clustering: Applied as an unsupervised clustering method to segment faculty into multi-dimensional performance cohorts without relying on prior manual labels, enabling administrators to detect latent structural barriers across cohorts.
 - c. Apriori Association Rule Mining: Utilized to discover transactional dependencies between Tri Dharma variables (e.g., extracting empirical rules showing that excessive teaching loads directly correlate with significant research output decline).
3. Semantic Knowledge Graph Layer: Maps algorithmic classifications against codified institutional ontologies and national promotion guidelines (PO PAK), providing transparent, explainable recommendations across competency improvement, functional promotion,

targeted mentoring, and institutional workload reallocation.

Suggested Evaluative Framework and Future Implementation Stages

To ensure that the Framework for Higher Education Human Resources for Lecturer Career Development transitions from conceptual design to impactful institutional practice, a structured implementation roadmap is established. The framework is designed not as an automated decision-maker, but as an explainable Decision Support System (DSS) collaborating with human administrative leadership. The planned development encompasses three stages: (1) formalizing higher education regulations into machine-readable Web Ontology Language (OWL) knowledge bases, (2) engineering a functional software prototype using Python and Neo4j, and (3) conducting empirical pilot testing on historical anonymized lecturer data across private higher education institutions in LLDIKTI Region II.

Several critical limitations of the current study must also be acknowledged: the bibliometric mapping was restricted to Scopus and Web of Science metadata; search queries were limited to English-language publications; the framework currently stands as a proposed conceptual architecture awaiting software prototyping; and recommendation validity remains contingent upon the completeness and lack of bias in underlying university databases.

Evaluation Based on Different Scenarios

The primacy of the Framework for Higher Education Human Resources for Lecturer Career Development lies in its capacity to understand the deeper context of lecturer performance and generate objective recommendations. To illustrate this workflow, two contrasting hypothetical profiles are evaluated.

Illustrative Scenario 1 (Lecturer A - Research-Heavy Profile): Lecturer A exhibits

outstanding research productivity with multiple Scopus-indexed publications, but falls short in accumulated teaching credits (Teaching KUM) required for promotion to Assistant Professor (*Lektor*) 300. Conventional evaluation systems simply issue a negative compliance status. In contrast, Framework for Higher Education Human Resources for Lecturer Career Development's Naïve Bayes classifier identifies high research readiness (94%), while the Knowledge Graph pinpoints the exact unfulfilled pedagogical prerequisite, recommending an optimized teaching schedule to achieve promotion readiness within 12 months.

Illustrative Scenario 2 (Lecturer B - Teaching-Trap Profile): Lecturer B has completed 8 years of service as a *Lektor* but has experienced promotion delays due to dormant publication output, caused by an excessive teaching burden of 20 credit units (SKS) and heavy administrative committee roles. In conventional reviews, Lecturer B is labeled as an underperforming lecturer. Framework For Higher Education Human Resources For Lecturer Career Development's K-Means clustering identifies Lecturer B within the Teaching-Trap cohort, while Apriori rule mining exposes that administrative overload directly suppresses research productivity. Framework For Higher Education Human Resources For Lecturer Career Development recommends that institutional leaders reduce Lecturer B's teaching load to the statutory minimum of 12 SKS, grant a research semester, and assign a senior mentor to co-author a publication, thereby unblocking their career progression toward Associate Professor (*Lektor Kepala*).

Preliminary Expert Consultation and Feedback

Beside establishing a theoretical foundation, the conceptual framework of the Framework for Higher Education Human Resources for Lecturer Career Development was subjected to preliminary expert

consultation with stakeholders at LLDIKTI Region II under the Ministry of Higher Education in Indonesia [28]. This consultative step verified that the conceptual logic corresponds to the practical realities of lecturer career monitoring across South Sumatra, Lampung, Bengkulu, and Bangka Belitung. The expert consultation yielded three essential qualitative findings: First, the computational logic of Framework For Higher Education Human Resources For Lecturer Career Development aligns with national standards for lecturer promotion (Lecturer Performance Load and PO PAK); second, the integration of predictive clustering and semantic knowledge graphs holds strong viability for reducing administrative barriers and subjective performance assessments in Private Higher Education Institutions; and third, stakeholders emphasized that the system must strictly function as an assistive Decision Support System that maintains human peer review and statutory governance.

CONCLUSION

Based on a systematic literature review and bibliometric analysis of exactly 400 documents from Scopus and Web of Science (2018–2024), this study identified a critical semantic-policy discrepancy between predictive machine learning algorithms and higher education human resource policies. AI has predominantly served as a descriptive monitoring tool rather than an objective, explainable career guidance mechanism. To address this research gap, this paper proposed the Framework for Higher Education Human Resources for Lecturer Career Development as a conceptual Decision Support System integrating Naïve Bayes classification, K-Means clustering, and Apriori association rules with an explainable Knowledge Graph layer. Preliminary expert consultation with LLDIKTI Region II confirmed the conceptual viability and regulatory alignment of the Framework in mitigating administrative bottlenecks. As a

proposed conceptual framework for Higher Education Human Resources for Lecturer Career Development establishes a theoretically grounded foundation for upcoming ontology codification, software prototyping, and empirical pilot evaluations in institutional higher education governance.

DECLARATIONS

Author Contributions: The first author contributed to the conceptualization, methodology, literature review, data collection, bibliometric analysis, visualization, and preparation of the original manuscript. The second author contributed to research supervision, methodological validation, critical review, and manuscript editing. The third author contributed to conceptual framework development, interpretation of findings, research supervision, and critical review of the manuscript. All authors reviewed and approved the final version of the manuscript.

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Conflict of Interest: The authors declare that they have no conflicts of interest related to this research.

Generative Artificial Intelligence Use Statement: Generative AI tools were used solely to assist with language refinement and grammatical improvement during manuscript preparation. All scientific content, research analysis, interpretation, and conclusions were reviewed and validated by the authors, who take full responsibility for the accuracy and integrity of the manuscript.

Ethics Approval and Informed Consent: This study primarily involved a systematic literature review and bibliometric analysis of previously published scientific literature. Therefore, formal ethics approval and informed consent were not required for the literature review component.

Data Availability: The bibliographic data analyzed in this study were obtained from Scopus and Web of Science. The processed datasets supporting the findings of this study are available from the corresponding author upon reasonable request, subject to applicable database licensing restrictions.

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