Explainable Artificial Intelegiant in Job Recommendation System Based on Outcome-Based Education Using Explainable Boosting Machine

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Abstract **The rapid advancement of artificial intelligence has led to the development of various career recommendation systems. However, most existing systems operate as black-box models, limiting transparency and user trust. This study proposes an explainable job recommendation system based on Outcome-Based Education (OBE) using the Explainable Boosting Machine (EBM). By leveraging Program Learning Outcomes (PLOs) and Course Learning Outcomes (CLOs) as primary features, the system provides accurate career recommendations while offering intrinsic interpretability.**

The model was trained on 60,000 student-job pairs derived from 769 student competency profiles and 3,352 job postings. The system was evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-Squared (R^2). Experimental results show that the proposed EBM-based model achieves excellent performance with MSE of 0.000002, RMSE of 0.0014, and R^2 of 0.9984. The model also demonstrates strong explainability through global and local feature importance analysis, allowing users to understand how each learning outcome contributes to the recommendation. This research bridges the gap between academic competencies and industry needs, contributing to more trustworthy and transparent AI systems in higher education.

Keywords : **Explainable Artificial Intelligence, Job Recommendation System, Outcome-Based Education, Explainable Boosting Machine, PLO, CLO**

I. INTRODUCTION

The development of artificial intelligence technology in career recommendation systems has shown significant progress in recent years. Various predictive models are now capable of processing large-scale data to provide personalized job suggestions to individuals. However, despite their high predictive capabilities, most of these recommendation systems remain black-box, making it difficult for users to understand the basis of the recommendations. [1] state that "Explainable recommendation systems attempt to develop models that generate not only high-quality recommendations but also intuitive explanations."

In Indonesia, universities are required to implement the Outcome-Based Education (OBE) approach as per Ministerial Regulation No. 53 of 2023. This approach emphasizes the achievement of Course Learning Outcomes (CLOs) and Program Learning Outcomes (PLOs) as the primary measure of learning success. However, the use of CLOs as the primary input in career recommendation systems remains very limited. Mapping graduate competencies with industry needs is often done manually or with simplistic approaches that underutilize the potential of available data. This creates a significant gap between learning outcomes in universities and the demands of the increasingly dynamic workforce.

artificial intelligence models such as neural networks and gradient boosting generally produce highly accurate predictions but are difficult to explain. [2] stated that "Despite widespread adoption, machine learning models remain mostly black boxes." This lack of transparency not only undermines student and lecturer trust in recommendation systems but also limits the ability of educational institutions to conduct evidence-based curriculum evaluations.

The need for transparent, explainable, and CLO-based career recommendation systems is increasingly pressing in today's era of digital transformation. The Explainable Artificial Intelligence (XAI) approach offers a solution to overcome the limitations of black-box models. [3] emphasized that "XAI proposes creating a suite of ML techniques that produce more explainable models while maintaining a high level of learning performance." By utilizing models such as the glass-box Explainable Boosting Machine (EBM), recommendation systems can provide accurate job suggestions while explaining the contribution of each CLO feature to the recommendation. This approach also supports the curriculum evaluation process by identifying competency gaps more objectively and measurably.

This research aims to fill this gap by proposing a career recommendation system that integrates the Outcome-Based Education (OBE) framework with Explainable Artificial Intelligence (XAI) techniques through the Explainable Boosting Machine (EBM) model. This system is expected to bridge the gap between academia and industry, providing career recommendations that are not only accurate but also transparent and accountable.

II. Related Work

Job recommendation systems have become an important application of artificial intelligence. Various approaches have been developed, from collaborative filtering to deep learning. However, most existing models still face transparency issues. [1] stated in their survey that "Explainable recommendation systems attempt to develop models that generate not only high-quality recommendations but also intuitive explanations." In recent years, research on explainable artificial intelligence (XAI) for recommendation systems has grown. [3] explain that XAI aims to create models that are not only accurate but also explainable, thereby increasing the trustworthiness and accountability of the system. [2] introduced LIME as a post-hoc method for explaining any model's predictions.

[4], in his thesis, "Explainable Artificial Intelligence in Job Recommendation Systems," specifically addresses this challenge in the career domain. He stated that "My inspiration for building a complete explainable job recommendation system came from a SaaS product provided by AOBG (Oracle Human Capital Management) and my growing interest in explainable AI." Tran emphasized the importance of transparency in job recommendation systems so that users, especially students, can understand the rationale behind recommendations and build trust in the system. Furthermore, [5] proposed an explainable reinforcement learning approach for long-term skill recommendations, considering the benefits and costs of learning. However, the integration of the Outcome-Based Education (OBE) framework with XAI techniques is still relatively rare. Most previous research has focused on user preferences or historical data, while the use of Course Learning Outcomes (CLO) as a basis for student competencies has not been explored in depth.

This research seeks to fill this gap by combi ning the OBE approach as a foundation for student competencies with an intrinsically interpretable Explainable Boosting Machine (EBM) model, resulting in career recommendations that are not only accurate but also transparent and accountable.

III. Methodology

This study employs a systematic methodology to develop an explainable career recommendation system based on Outcome-Based Education (OBE) principles, utilizing the Explainable Boosting Machine (EBM). The system architecture follows a two-stage design: 1. a retrieval stage that ranks job candidates based on cosine similarity, and 2. a decomposition stage where the EBM explains the relative contribution of each feature to the aggregate score of each ranked job. The final ranking is determined solely by the similarity level; the EBM does not alter the ranking but instead provides transparency regarding its composition. The overall process comprises six main stages: data collection, preprocessing and NLP, feature engineering, model selection and justification, EBM modeling, and the alignment of explainability with system outputs. The complete workflow is illustrated in Figure 1.

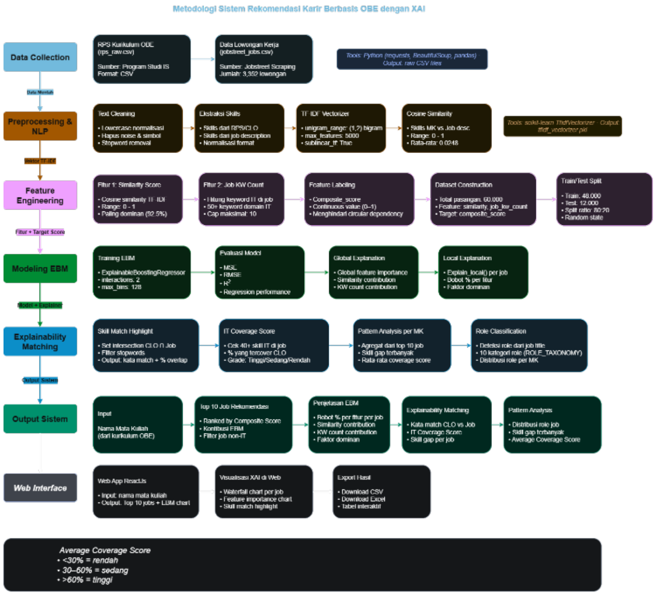

Figure 1. Methodology Chart

A. Data Collection

The data used in this study were collected from two primary sources. The first source consisted of curriculum documents—specifically, Semester Learning Plans (RPS)—from the Information Systems study program, detailing Program Learning Outcomes (PLO) and Course Learning Outcomes (CLO) for 48 courses. The second source comprised actual job vacancy data obtained from Jobstreet, covering 3,352 job advertisements. Both datasets were stored in CSV format for further processing.

The 48 courses were then categorized into three groups based on the IS2020 curriculum guidelines: IT-Specific (15 courses), IT-General (21 courses), and Non-IT (12 courses). This categorization served to limit the aggregate gap analysis to the 36 IT-related courses, thereby avoiding confusion with courses unrelated to technical competencies (e.g., Pancasila and Indonesian Language).

B. Preprocessing and NLP

At this stage, text data from CLO and job descriptions undergo several preprocessing steps, including lowercase normalization, the removal of noise and symbols, and stopword removal.

To address the vocabulary gap between academic CLO language and industry terminology (e.g., "data dasar" in CLOs versus "basis data" in job postings), a curated translation dictionary (CLO_TO_INDUSTRY) comprising over 100 term mappings is applied prior to skill matching. This dictionary translates Indonesian academic phrases into industry-standard technical terms across various domains, including programming, databases, networking, cloud computing, and enterprise architecture. This approach is based on prior findings regarding the vocabulary gap between academic and industry terminology in software engineering education.

Skill entities are then extracted from the normalized CLO documents and job descriptions using a curated dictionary of IT skill terms (IT_SKILL_TERMS).

TF-IDF vectorization is applied to convert the text into numerical vectors using unigrams and bigrams, with a maximum of 5,000 features. The formula used for TF-IDF is as follows:[6]

$$wt, d = tft, d \times log(dftN)$$

Subsequently, cosine similarity was calculated between course learning outcomes and job descriptions to measure relevance. The cosine similarity formula used is as follows [7]

$$\mathrm{sim}(A, B) = \frac{A \cdot B}{||A||\,||B||}$$

C. Feature Engineering

Based on TF-IDF vectors and skill extraction results, two primary retrieval features were designed:

1. Similarity Score: The cosine similarity value between the CLO and the job description (range 0–1).
2. Job Keyword Count: The number of IT-related keywords found in the job description, up to a maximum of 10.

Candidate job postings are filtered to retain only those containing at least four keywords, ensuring that low-relevance postings are eliminated prior to the ranking stage. These two features are combined into a single composite score using a multiplicative boosting formulation:

$$\mathrm{Composite\_scor} = \mathrm{Similarity} \times (1 + \frac{\mathrm{Job\_kw\_count}}{10})$$

This formulation adopts the multiplicative reinforcement principle underlying the BM25 family of ranking functions, where similarity serves as the primary relevance signal and keyword count acts as a bounded reinforcement factor (ranging from 1.0x to 2.0x).[8] This design intentionally maintains similarity as the dominant term while avoiding arbitrarily assigned manual weights.

The dataset was constructed with a total of 60,000 job similarity pairs and split into training (80%) and testing (20%) sets.

D. Modelling

The primary model employed in this study is the Explainable Boosting Machine (EBM), implemented using the ExplainableBoostingRegressor from the InterpretML library. EBM is a "glass-box" model based on Generalized Additive Models (GAM) [9] that delivers high accuracy while maintaining inherent interpretability. Unlike post-hoc explanation methods—such as LIME or SHAP—which estimate feature contributions for opaque models, EBM produces additive and exact feature attributions as an intrinsic characteristic of its architecture.[10] [11]

Key hyperparameters used were:

1) Maximum interactions: 1
2) Maximum bins: 128
3) Learning rate: 0.01
4) Maximum rounds: 3000

Model performance was evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 score.

E. Explainability and Matching

After the model is trained, interpretability analysis is conducted at two levels:

1) Global Explanation: The importance of features across trained models, obtained via explain_global().
2) Local Explanation: The contribution of each feature to individual job recommendations, obtained via explain_local().

Independently from the EBM decomposition, an explainability matching process was conducted to assess curriculum readiness. IT Coverage Score was computed following the Precision formulation from Information Retrieval.[7] :

$$Coverage\ Score = \frac{|CLO \cap Job\ IT\ Skills|}{|\mathrm{Job\ IT\ Skills}|} \times 100\%$$

Here, "Job IT Skills" refers to the set of specific IT terms identified in job descriptions via the IT_SKILL_TERMS dictionary, with the intersection representing terms that also appear in the relevant CLOs following vocabulary normalization (Section III-B). This metric operates independently of the EBM model and provides a post-hoc explanation of the alignment between the curriculum and the industry.

It involves identifying skills gaps, highlighting skill matches, and classifying job roles into the same 10 matching categories.

F. The final output of the system is a web-based application built with React.js and a FastAPI backend. Users can select a course name from the OBE curriculum, and the system displays:

1. Top-10 job recommendations ranked by similarity score,
2. EBM local and global explanation (feature contribution breakdown),
3. Skill match highlighting and skill gap identification, and
4. IT Coverage Score visualization per course and in aggregate across IT-related courses.

IV. Result

This section presents the experimental results of the developed explainable career recommendation system. The system was evaluated on multiple aspects, including model performance, feature importance, explanation quality, and practical output relevant to curriculum evaluation.

1. Model Performance

   The EBM model was trained using 48,000 data pairs and evaluated on 12,000 unseen test pairs. The model achieved the following performance metrics:

   1. Mean Squared Error (MSE): 0.000002
   2. Root Mean Squared Error (RMSE): 0.0014
   3. R^2 Score: 0.9984

   The exceptionally high R^2 value (0.9984) indicates that the model explains nearly all variance in the composite score. This result is expected and does not indicate overfitting. As an additive model based on Generalized Additive Models (GAM), EBM explicitly decomposes the prediction into the sum of individual feature contributions rather than discovering complex hidden interactions. Because the composite score target was explicitly constructed from the same two features used for prediction (Section III-C), a high R^2 reflects successful decomposition of a transparent, intentionally designed relationship rather than data leakage in the conventional sense. This distinction is critical: unlike the earlier classification attempt, which produced a misleadingly perfect AUC due to circular dependency in label construction, this regression formulation does not require an independent ground truth and therefore avoids the same validity threat. [12] [11].

2. Global Feature Importance

   Global explanation from the EBM model reveals a clear dominance of features, as shown in Figure 2:

   1. Cosine Similarity Score (TF-IDF based): 92.5% contribution
   2. Job Keyword Count (IT domain keywords): 7.5% contribution

   This result validates the system design choice to preserve similarity as the dominant ranking signal (Section III-C). Semantic similarity between CLOs and job descriptions is the primary driver in determining job relevance, while explicit IT keyword matching serves as a bounded reinforcing signal. This finding is consistent across nearly all individual job recommendations examined, as the composite score formula constrains the keyword count contribution to a narrow multiplicative range (1.0×–2.0×), limiting the extent to which local feature contributions can diverge from the global pattern a characteristic acknowledged as a limitation in Section VI.

3. Recommendation Output Examples

   Table 1 presents an example of the system output for the course "Jaringan Komputer" (Computer Networks)..

Rank	Job Title	Similarity	IT key	EBM Similarity
1	IT Support	15%	4/10	97.3%
2	Middle Web Developer	14%	4/10	97.3%
3	Engineer on Site	11%	5/10	94.4%

Table 1. Top 3 Recommendation for “Computer Networks”

The local explanation shows that high cosine similarity driven by shared terminology such as "jaringan," "network," and "layer" between the CLO and job descriptions contributes dominantly to the composite score of top-ranked recommendations, consistent with the global feature importance pattern reported above.

4. Gap Analysis Results

   One of the most significant findings of this study is the competency gap between the OBE curriculum and industry requirements. Following a refinement of the CLO-to-industry vocabulary mapping (Section III-B), the analysis across 36 IT-related courses in the Information Systems program shows:

   1) Average IT Coverage Score: 11.93% (pooled mean across 360 course-job observations)
   2) Number of courses with coverage > 0%: 31 out of 36 (86.1%)
   3) Number of courses with coverage = 0%: 5 out of 36 (13.9%)

   The largest skill gaps, measured by the number of IT-related courses in which each skill was identified as missing, were found in:

1. PostgreSQL (gap in 33/36 courses)
2. SQL (gap in 32/36 courses)
3. MySQL (gap in 32/36 courses)
4. Python Programming (gap in 30/36 courses)

The five courses with zero coverage include both courses with inherently conceptual learning outcomes (e.g., Adoption of Information Technology, which focuses on innovation diffusion theory rather than technical implementation) and courses where technical competencies are implicit but not explicitly reflected in the CLO wording (e.g., Information Security). This distinction suggests that zero-coverage findings require course-level interpretation rather than uniform treatment, supporting curriculum evaluation at the level of individual courses rather than relying solely on the aggregate average.

These findings provide empirical evidence for curriculum improvement, particularly highlighting database-related technologies as a priority area for CLO revision across the majority of IT courses in the program.

5. System Interface

   The system has been implemented as a web application using a React.js frontend and a FastAPI backend. The interface consists of three main views:

   1 Dashboard: Allows course selection and displays global curriculum metrics alongside Top-10 job recommendations with EBM

feature contribution breakdowns for the selected course..

2 Gap Analysis: Visualizes skill coverage and competency gaps through macro-level distribution charts, a per-course coverage table with categorical filtering (IT-Specific, IT-General, Non-IT), and a heatmap matrix of skill gap frequency across IT-related courses.

3 Explainability View: Presents local EBM feature contribution for a selected course-job pair alongside global feature importance and content matching analysis, including matched skills and outstanding skill gaps.

V. Conclusion

This research has successfully developed an explainable career recommendation system based on Outcome-Based Education (OBE) using the Explainable Boosting Machine (EBM) as a decomposition model. By integrating Course Learning Outcomes (CLOs) as the primary input, the system generates OBE-aligned job recommendations while providing transparent explanations of each feature's contribution toward the ranking score through both global and local EBM explainability..

The developed methodology encompasses systematic data collection from curriculum documents (48 courses) and job postings (3,352 vacancies from Jobstreet Indonesia), TF-IDF-based text processing with vocabulary normalization to bridge academic-industry terminology gaps, composite score engineering, EBM regressor training, and a two-level explainability analysis. A key methodological contribution of this study is the resolution of circular dependency in supervised labeling a fundamental validity threat in recommendation systems that lack independent ground truth by reframing EBM as a score decomposer rather than a binary classifier.

The experimental results demonstrate that the EBM model achieves high decomposition accuracy ($R^2 = 0.9984$, RMSE = 0.0014), which is expected given that the target composite score was explicitly constructed from the same features used for prediction. More substantively, the gap analysis reveals critical curriculum misalignments across the Information Systems program: PostgreSQL, SQL, and MySQL are absent from the CLOs of at least 32 of 36 IT-related courses, and the overall pooled mean IT Coverage Score is only 11.93%. This finding provides evidence-based insight for curriculum evaluation, with the analysis further indicating that improvement priorities should be identified at the level of individual courses rather than through aggregate averages alone.

In conclusion, this research contributes to the development of trustworthy AI systems in education by demonstrating that XAI techniques — specifically EBM — can be applied not only for prediction but also for transparent decomposition of ranking scores in curriculum-industry alignment analysis. The identified skill gaps provide actionable evidence for study programs to evaluate and revise their OBE curricula toward greater industry relevance.

VI. Limitations and Future Work

This research has several limitations that should be acknowledged. First, the absence of an independent ground truth prevents absolute validation of recommendation quality; the system can only be evaluated in relative terms determining which job ranks higher relative to others for a given course rather than confirming whether a recommendation is objectively correct. Second, the composite score formulation constrains local EBM explanations to a narrow range, as similarity is designed to dominate the score by construction; this limits the extent to which local feature contributions can meaningfully diverge across individual recommendations. Third, the CLO-to-industry vocabulary mapping was manually curated and, while substantially improved through iterative refinement, remains inherently non-exhaustive. Fourth, the dataset is currently limited to a single Information Systems study program, and no formal usability evaluation was conducted with faculty or students.

Future work should focus on integrating semantic embedding models (e.g., IndoBERT) to more comprehensively address the vocabulary gap between academic CLO language and industry terminology, beyond what manual dictionary mapping can achieve. Further work may also explore comparative analysis between EBM and post-hoc explanation methods such as SHAP to evaluate the consistency and depth of feature attributions. Additionally, expanding the dataset across multiple study programs, conducting structured usability studies with faculty and students, and periodically updating job posting data would strengthen the generalizability and practical applicability of the system.

References

[1] Y. Zhang and X. Chen, "Explainable recommendation: A survey and new perspectives," Mar. 11, 2020, *Now Publishers Inc*. doi: 10.1561/1500000066.

[2] M. T. Ribeiro, S. Singh, and C. Guestrin, "'Why should i trust you?' Explaining the predictions of any classifier," in *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Association for Computing Machinery, Aug. 2016, pp. 1135–1144. doi: 10.1145/2939672.2939778.

[3] A. B. Arrieta *et al.*, "Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI," Dec. 2019, [Online]. Available: http://arxiv.org/abs/1910.10045

[4] T. Hoang and A. Tran, "MSc Business Information Technology Final Project Explainable Artificial Intelligence in Job Recommendation Systems," 2023.

[5] Y. Sun, Y. Ji, H. Zhu, F. Zhuang, Q. He, and H. Xiong, "Market-aware Long-term Job Skill Recommendation with Explainable Deep

Reinforcement Learning," *ACM Trans. Inf. Syst.*, vol. 43, no. 2, Jan. 2025, doi: 10.1145/3704998.

[6] C. B. Gerard Salton, "Term Weighting Approaches in Automatic Text Retrieval," 1987.

[7] C. D. . Manning, Prabhakar. Raghavan, and Hinrich. Schütze, *Introduction to information retrieval*. Cambridge University Press, 2009.

[8] S. E. Robertson and S. Walker, "Some Simple Effective Approximations to the 2-Poisson Model for Probabilistic Weighted Retrieval."

[9] T. Hastie, "Generalized Addict Models," 1986.

[10] Qiang. Yang, *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2012.

[11] H. Nori, S. Jenkins, P. Koch, and R. Caruana, "InterpretML: A Unified Framework for Machine Learning Interpretability," Sep. 2019, [Online]. Available: http://arxiv.org/abs/1909.09223

[12] Qiang. Yang, *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2012.