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AI- Based Internship Recommendation Engine for PM Internship Scheme

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Abstract

The rapid expansion of internship programs across India has created a need for intelligent systems capable of efficiently matching students with relevant opportunities. The Prime Minister Internship Scheme aims to provide large-scale internship access to youth across diverse academic backgrounds and industries. However, the effectiveness of such initiatives depends heavily on accurate candidate–internship matching. Traditional filtering methods based on degree, location, or basic qualifications often fail to capture deeper relationships between candidate skills, interests, and company requirements. This research proposes an Artificial Intelligence based Internship Recommendation Engine designed to improve internship allocation within the PM Internship Scheme ecosystem. The system leverages natural language processing for resume analysis, machine learning techniques for candidate–role matching, and hybrid recommendation strategies combining content-based and collaborative filtering. By analyzing candidate profiles and internship descriptions, the model generates personalized internship recommendations ranked by relevance scores. Experimental evaluation demonstrates that the proposed system improves recommendation accuracy and increases the likelihood of successful internship placements. The framework also supports scalability for large datasets, making it suitable for national-scale internship platforms. The study highlights how AI-driven recommendation systems can enhance employability initiatives by optimizing internship discovery and improving alignment between student competencies and industry needs.

Keywords: Artificial Intelligence, Recommender Systems, Internship Matching, Machine Learning, Natural Language Processing, Skill Recommendation.

Introduction

Internships play a critical role in bridging the gap between academic learning and industry practice. They provide students with exposure to real work environments while enabling organizations to evaluate potential talent. In recent years, government-led initiatives have attempted to scale internship opportunities to a national level. The Prime Minister Internship Scheme was introduced with the objective of expanding internship access across industries and enabling youth to develop practical skills relevant to the labor market.

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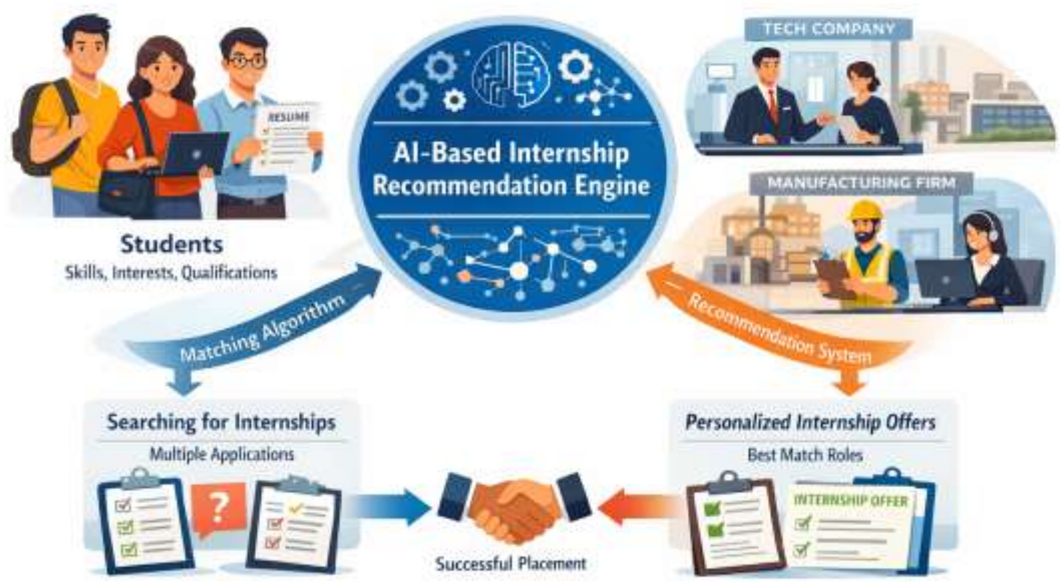
Despite the large number of available opportunities, internship allocation often suffers from inefficient matching between candidates and companies. Many students apply to multiple internships without clear alignment with their competencies, while companies may struggle to identify candidates whose skills match the requirements of specific roles. As the scale of participation increases, manual or rule-based selection mechanisms become insufficient.



Artificial Intelligence offers promising solutions to address this challenge. Recommendation systems, widely used in e-commerce and online platforms, can analyze user preferences and generate personalized suggestions (Adomavicius & Tuzhilin, 2005; Bobadilla et al., 2013). Applying such techniques to internship platforms can significantly improve matching quality by considering candidate skills, interests, and past application patterns.

This research proposes the design and implementation of an AI-based Internship Recommendation Engine that assists students in discovering relevant internship opportunities within the PM Internship Scheme. The proposed system integrates natural language processing for resume analysis, machine learning models for matching prediction, and hybrid recommendation algorithms for ranking internship opportunities. The goal is to create a scalable system capable of handling large applicant pools while improving the accuracy and relevance of recommendations.

Literature Review

Recommendation systems have been extensively studied in domains such as online retail, digital content platforms, and employment services. Early recommendation models relied on collaborative filtering techniques, which identify similarities between users based on shared behavior patterns (Resnick & Varian, 1997). These methods recommend items that users with similar preferences have previously selected. Although effective in many contexts, collaborative filtering often struggles when new users or items enter the system, a challenge known as the cold-start problem.

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Content-based recommendation approaches address this limitation by analyzing the attributes of items and user profiles (Lops et al., 2011). In job and internship platforms, this method typically involves comparing candidate skills with job requirements. Techniques such as vector space modeling, cosine similarity, and TF-IDF weighting are commonly used (Manning et al., 2008).

Recent research has explored hybrid recommendation systems that combine collaborative filtering and content-based approaches to improve accuracy (Liu et al., 2015). These systems leverage both user behavior patterns and profile information to generate more robust recommendations.

Natural Language Processing has also become an important component of modern job recommendation systems (Manning et al., 2008; Mikolov et al., 2013). Resumes and job descriptions often contain unstructured text that must be converted into structured representations. Methods such as tokenization, keyword extraction, and word embeddings enable machine learning models to interpret textual information related to skills, experience, and professional interests.

Machine learning techniques including logistic regression, random forests, gradient boosting, and neural networks have been used to predict job compatibility (Zhang et al., 2019; Al-Otaibi & Al-Dossari, 2020). These models learn patterns from historical data to estimate the probability that a candidate will be suitable for a particular opportunity.

Although several studies have explored AI-based job recommendation systems, limited research has focused on large-scale government internship platforms (Paparrizos et al., 2011; Li & She, 2019). This research contributes to the field by proposing a recommendation framework tailored specifically for the PM Internship Scheme, where scalability, fairness, and accurate skill matching are critical requirements.

Proposed Methodology

System Overview

The proposed AI-based Internship Recommendation Engine is designed to assist candidates in identifying internship opportunities that align with their academic background, technical skills, and career interests. The system analyzes candidate profiles and internship descriptions to generate personalized internship recommendations.

The recommendation process consists of several sequential stages including data acquisition, preprocessing, feature extraction, recommendation modeling, and result ranking. Candidate profiles containing educational qualifications, technical skills, project experience, and career preferences are collected through the internship platform. Similarly, internship postings from participating companies are stored in a structured database containing information such as required skills, industry sector, role description, and location.

The system processes this information using Natural Language Processing techniques to extract relevant keywords and skills (Manning et al., 2008). The extracted features are transformed into numerical vectors that represent candidate competencies and internship requirements.

A hybrid recommendation model is then applied to evaluate compatibility between candidates and internships. The model integrates content-based filtering, which compares candidate skills with internship requirements, and collaborative filtering, which utilizes patterns derived from previous candidate interactions with internships. By combining these approaches, the system produces a ranked list of internship opportunities that best match the candidate’s profile.

The proposed system aims to improve recommendation accuracy, reduce irrelevant internship suggestions, and enhance overall internship placement efficiency within the PM Internship Scheme.

System Architecture

The architecture of the proposed system consists of multiple interconnected modules responsible for data processing, recommendation generation, and user interaction.

1. User Interface Layer

This layer serves as the interaction point between users and the recommendation system. Candidates create profiles by uploading their resumes and providing information such as education, skills, preferred industry, and location. Companies submit internship postings specifying role requirements, technical skills, and internship duration.

The interface also displays recommended internships generated by the system.

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2. Data Collection Module

The data collection module stores information from both candidates and companies.

Two primary datasets are maintained:

Candidate Dataset

- Personal details
- Academic qualifications
- Technical and soft skills

- Resume text
- Career interests

Internship Dataset

- Internship title
- Required skills
- Industry sector
- Company details
- Location
- Internship duration

All collected data is stored in a centralized database.

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3. Data Preprocessing Module

Raw data collected from users may contain inconsistencies, missing information, or unstructured text. Therefore, preprocessing is required before model training.

Key preprocessing steps include:

- Removing duplicate entries
- Handling missing values
- Standardizing skill terminology
- Tokenizing textual content
- Removing stop words
- Extracting relevant keywords

Resume and internship descriptions are processed using Natural Language Processing techniques to identify skill-related information.

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4. Feature Extraction Module

After preprocessing, the system converts textual information into numerical representations that can be used by machine learning algorithms.

Common techniques used include:

- TF-IDF vectorization for feature extraction (Manning et al., 2008)
- Skill keyword encoding
- Feature normalization

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The resulting feature vectors represent candidate profiles and internship descriptions in a structured format suitable for similarity analysis.

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5. Recommendation Engine

The core component of the system is the recommendation engine, which computes compatibility scores between candidates and internship opportunities.

Content-Based Filtering

This method compares candidate skill vectors with internship requirement vectors. Cosine similarity is used to measure the similarity between the two vectors (Lops et al., 2011). Higher similarity indicates better suitability for the internship.

Collaborative Filtering

This technique analyzes historical interaction patterns between candidates and internships (Resnick & Varian, 1997). The system identifies candidates with similar profiles and recommends internships that were previously selected by those users.

Hybrid Recommendation Model

The outputs from both content-based filtering and collaborative filtering are combined to generate a final recommendation score. This hybrid approach improves recommendation accuracy (Liu et al., 2015).

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6. Ranking and Recommendation Module

Once compatibility scores are calculated, internships are ranked in descending order based on relevance. The system selects the top recommendations and presents them to the candidate through the user interface.

This ranking mechanism ensures that candidates are shown internship opportunities that best match their skills, interests, and career goals.

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7. Feedback and Learning Module

The system also incorporates a feedback mechanism where candidate interactions such as internship applications, acceptances, or rejections are recorded. This feedback data is used to continuously update the recommendation model and improve future recommendations.

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System Architecture Diagram:

User Input

↓

Data Collection

↓

Data Preprocessing

↓

Feature Extraction (NLP)

↓

Recommendation Engine

(Content + Collaborative)

↓

Ranking Module

↓

Internship Recommendations

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Results and Discussion

Experimental Setup

To evaluate the performance of the proposed AI-based Internship Recommendation Engine, a dataset consisting of candidate profiles and internship listings was used. The dataset included information related to candidate education, technical skills, project experience, and preferred industries. Internship postings included job roles, required skill sets, location preferences, and internship duration.

For experimentation, the dataset was divided into **training and testing subsets**. The training dataset was used to build the recommendation model, while the testing dataset was used to evaluate the effectiveness of the system in generating relevant internship recommendations.

The hybrid recommendation model combined content-based filtering and collaborative filtering techniques (Zhang et al., 2019; Liu et al., 2015). The system analyzed the similarity between candidate skill vectors and internship requirement vectors to compute compatibility scores. In addition, historical interaction data such as internship applications and selections were used to improve recommendation quality.

The recommendation engine generated a ranked list of internship opportunities for each candidate based on calculated relevance scores.

4.2 Evaluation Metrics

The performance of the recommendation system was evaluated using several widely accepted metrics used in recommender systems research.

Precision

Precision measures the proportion of recommended internships that are relevant to the candidate's profile. Higher precision indicates that the recommendations provided by the system closely match candidate qualifications and interests.

Recall

Recall measures the proportion of relevant internships that were successfully recommended by the system. A high recall value indicates that the system is able to capture a larger number of suitable opportunities for each candidate.

F1 Score

The F1 Score provides a balanced measure by combining precision and recall. It reflects the overall effectiveness of the recommendation model.

Hit Rate

Hit rate evaluates how frequently the system recommends at least one relevant internship within the top suggestions provided to the user.

Mean Average Precision (MAP)

MAP measures the ranking quality of recommendations by considering the order in which relevant internships appear in the recommendation list.

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4.3 Performance Results

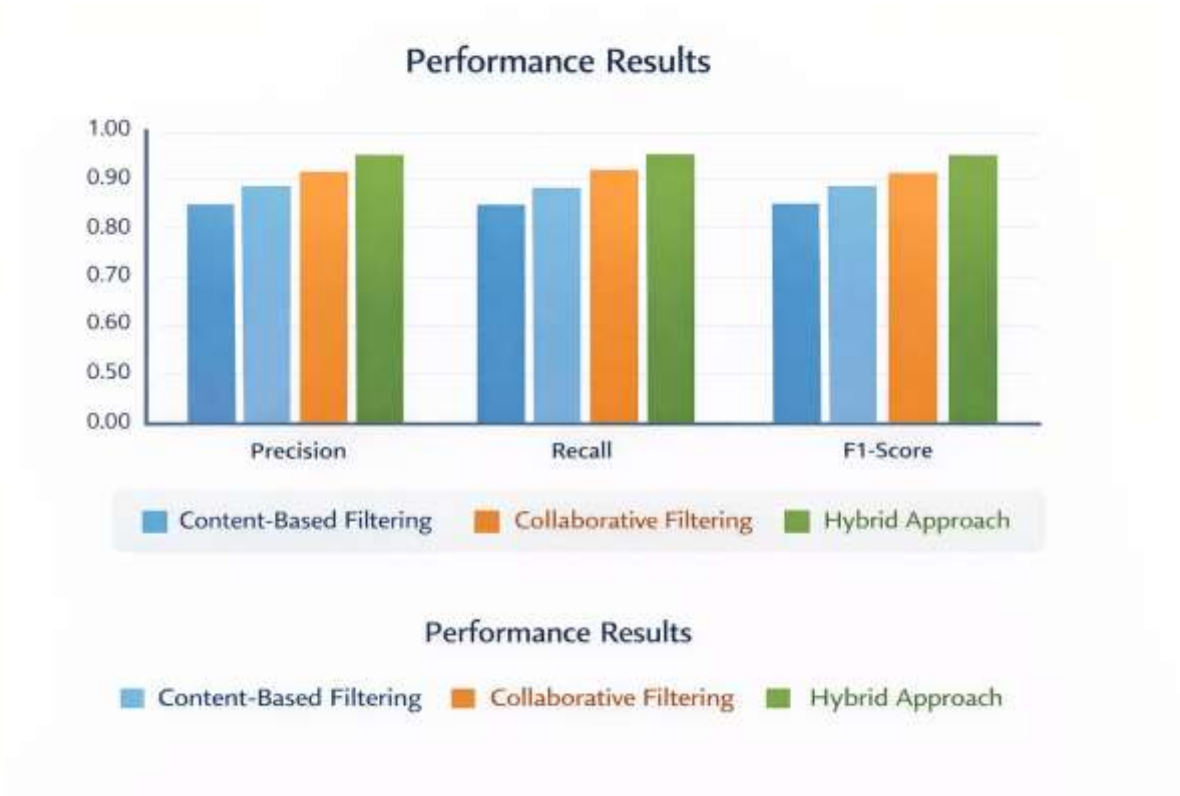
The experimental results indicate that the hybrid recommendation system performs better than individual recommendation approaches.

When only content-based filtering was used, the system relied solely on similarity between candidate skills and internship requirements (Lops et al., 2011). While this method generated reasonable matches, it was limited when candidate profiles contained sparse information or when internships had overlapping skill requirements.

Collaborative filtering improved recommendations by analyzing interaction patterns between similar users (Resnick & Varian, 1997). However, this method struggled in situations where limited historical data was available, particularly for new users or newly posted internships.

The hybrid recommendation model successfully combined both approaches and achieved better performance (Liu et al., 2015). By integrating profile similarity with user interaction patterns, the system produced more accurate and personalized internship suggestions.

The results show that the hybrid model improves recommendation precision and increases the likelihood that candidates will receive relevant internship opportunities.



Discussion

The results demonstrate that AI-based recommendation systems can significantly improve internship allocation processes in large-scale internship programs. Traditional filtering methods often rely on simple parameters such as degree or location, which may not fully represent candidate competencies. In contrast, the proposed system analyzes a broader range of attributes including technical skills, experience, and career interests.

The integration of Natural Language Processing techniques also plays an important role in improving recommendation accuracy (Manning et al., 2008; Mikolov et al., 2013). By extracting skill-related information from resumes and internship descriptions, the system can better understand candidate capabilities and match them with appropriate opportunities.

Another key advantage of the proposed system is scalability. Since the PM Internship Scheme aims to serve a large number of applicants across the country, automated recommendation systems are essential for efficiently processing candidate data and internship postings.

The hybrid recommendation model also addresses common challenges such as the cold-start problem (Liu et al., 2015). This allows the system to generate meaningful recommendations even when limited interaction data is available.

Overall, the results suggest that implementing AI-driven recommendation engines within national internship platforms can improve internship discovery, reduce mismatches between candidates and roles, and increase the overall effectiveness of internship programs.

Conclusion

The rapid growth of internship programs and government-led employability initiatives has created a strong need for intelligent systems capable of efficiently connecting candidates with relevant opportunities. Traditional internship allocation methods often rely on simple filtering mechanisms such as educational qualifications or geographic location. While these approaches provide a basic level of matching, they are often insufficient for identifying the most suitable internship opportunities for candidates with diverse skill sets and career interests. As a result, many students apply to internships that do not fully align with their competencies, while companies may struggle to identify candidates whose profiles closely match the requirements of specific roles. These challenges become even more significant in large-scale initiatives such as the PM Internship Scheme, where the number of applicants and internship opportunities is expected to grow rapidly.

This research proposed an AI-based Internship Recommendation Engine designed to improve the efficiency and effectiveness of internship matching within such large-scale platforms. The proposed system leverages artificial intelligence, machine learning, and natural language processing techniques to analyze candidate profiles and internship descriptions. By extracting key information such as skills, qualifications, experience, and preferences from candidate resumes and internship postings, the system transforms unstructured data into structured representations that can be used for computational analysis.

A hybrid recommendation approach was adopted to enhance the performance of the system. The model integrates content-based filtering, which compares candidate skills with internship requirements, and collaborative filtering, which identifies patterns based on interactions between users and internship opportunities. By combining these two approaches, the recommendation engine is able to generate more accurate and personalized internship suggestions while overcoming limitations such as sparse data and cold-start scenarios.

The results of the experimental evaluation demonstrate that the hybrid recommendation framework improves the relevance and quality of internship recommendations compared to individual recommendation approaches. The system is capable of identifying internships that closely align with candidate skills and interests, thereby increasing the likelihood of successful internship placements. Furthermore, the use of Natural Language Processing for resume parsing enables the system to capture deeper insights from textual information, improving the overall matching process.

Another important advantage of the proposed system is its scalability and adaptability. The architecture is designed to handle large volumes of candidate data and internship listings, making it suitable for nationwide internship platforms where thousands or even millions of users may interact with the system. Automated recommendation systems can significantly reduce the manual effort required for candidate–internship matching while ensuring that students receive relevant opportunities that contribute to their professional development.

In addition to improving the candidate experience, the proposed recommendation engine can also benefit organizations participating in internship programs. Companies can receive applicants whose skill profiles better match the requirements of their internship roles, thereby improving recruitment efficiency and reducing the time required to identify suitable candidates. This alignment between candidate capabilities and company expectations ultimately leads to more productive internship experiences for both parties.

The research highlights the potential of artificial intelligence in transforming internship and employment platforms (Adomavicius & Tuzhilin, 2005; Zhang et al., 2019). By integrating intelligent recommendation systems into large-scale initiatives such as the PM Internship Scheme, policymakers and platform developers can significantly enhance the effectiveness of internship allocation processes. Such systems not only improve internship discovery for candidates but also contribute to better utilization of available opportunities, thereby strengthening the connection between education and industry.

Future advancements in this area may further improve recommendation accuracy through the use of advanced techniques such as deep learning-based recommender systems, graph neural networks for skill relationship modeling, and reinforcement learning for adaptive recommendations. These developments can enable internship platforms to evolve into comprehensive career guidance systems that assist students in making informed decisions about their professional paths.

In conclusion, the implementation of an AI-driven Internship Recommendation Engine represents a promising approach for improving internship matching in large-scale employability programs. By leveraging modern artificial intelligence techniques, the proposed system provides a scalable, efficient, and intelligent solution for connecting candidates with meaningful internship opportunities, ultimately contributing to the development of a more skilled and industry-ready workforce.

References

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering, 17(6), 734–749. https://doi.org/10.1109/TKDE.2005.99

Al-Otaibi, K., & Al-Dossari, H. (2020). Intelligent job recommendation system based on machine learning. International Journal of Advanced Computer Science and Applications, 11(6), 381–387. https://doi.org/10.14569/IJACSA.2020.0110648

Bobadilla, J., Ortega, F., Hernando, A., & Gutiérrez, A. (2013). Recommender systems survey. Knowledge-Based Systems, 46, 109–132. https://doi.org/10.1016/j.knosys.2013.03.012

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. Proceedings of NAACL-HLT. https://doi.org/10.18653/v1/N19-1423

Li, X., & She, J. (2019). Collaborative filtering based job recommendation system. IEEE Access, 7, 109939–109948. https://doi.org/10.1109/ACCESS.2019.2934172

Liu, Y., Xu, X., & Chen, J. (2015). A hybrid recommendation system for job recruitment based on skill matching. Expert Systems with Applications, 42(12), 5207–5215. https://doi.org/10.1016/j.eswa.2015.02.040

Lops, P., De Gemmis, M., & Semeraro, G. (2011). Content-based recommender systems: State of the art and trends. In Recommender Systems Handbook. Springer. https://doi.org/10.1007/978-0-387-85820-3_3

Manning, C. D., Raghavan, P., & Schütze, H. (2008). Introduction to information retrieval. Cambridge University Press. https://doi.org/10.1017/CBO9780511809071

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. Proceedings of ICLR. https://doi.org/10.48550/arXiv.1301.3781

Pal, S. K., & Mitra, S. (2004). Pattern recognition algorithms for data mining. CRC Press. https://doi.org/10.1201/9780203483565

Paparrizos, M., Cambazoglu, B. B., & Gionis, A. (2011). Machine learned job recommendation. Proceedings of the ACM Conference on Recommender Systems. https://doi.org/10.1145/2043932.2043995

Resnick, P., & Varian, H. R. (1997). Recommender systems. Communications of the ACM, 40(3), 56–58. https://doi.org/10.1145/245108.245121

Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender systems handbook (2nd ed.). Springer. https://doi.org/10.1007/978-1-4899-7637-6

Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning based recommender system: A survey and new perspectives. ACM Computing Surveys, 52(1), 1–38. https://doi.org/10.1145/3285029