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AI-Enhanced Campus Recruitment Portal for Direct Student-Recruiter Interaction and Smart Resume Enhancement

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ABSTRACT

This work provides an AI-powered campus recruitment tool designed to automate the engagement processes in university recruitment. It seeks to solve some of the major challenges found in recruitment processes, such as skill-role mismatches, delays from manual screening, scalability issues, and recruitment bias [1]. The tool employs ML generalisation for candidate-job matching and feedback loops, as well as credential parsing and improvement using NLP [2][7][11]. Due to the work's cloud-native model, designed with Docker and Kubernetes, it provides concurrent cross-institutional recruitment at scale and with high performance [5]. Incorporating AI for resume boosting reduces the time spent reviewing resumes in the hiring process by almost 60%. Additionally, it increases match improvement and graduate employability rates. Thanks to the system's modular structure, it is compatible with large company HR systems, making it applicable to hiring in both educational and corporate settings [9].

Index Terms: *AI, machine learning, NLP, campus hiring, recruitment automation, resume enhancement, HR technology.*

1. INTRODUCTION

Systemic issues affecting campus hiring continue to lead to prolonged selection processes and to constraints on students' access. Standard processes still treat applications and CVs if there are people doing it. This leads to scaling issues, resulting in longer hiring processes and workflow bottlenecks [10]. The gap between what employers want and how candidates can write resumes, if at all, leaves students without the tools to present their capabilities and skills [11]. The lack of transparent processes results in dissatisfaction among both students and recruiters. Recent inroads in AI and machine learning (ML), which we present as solutions to those issues. We see that AI is taking over routine screening tasks, reducing bias, and improving decision-making accuracy [1]. Also, we note that, in terms of job-to-candidate match-up, we have improved it with ML-based models, and we are using NLP for In-depth analysis of resumes and for a report-like output that, in turn, is used for better content generation [2][7].

The AI-Enhanced Campus Recruitment Platform introduced in this study integrates automation, intelligent analytics, and user-friendly design to improve efficiency, transparency, and overall hiring effectiveness.

2. RELATED WORK

A. Traditional Campus Recruitment Systems

Current university recruitment platforms are more concerned with disseminating information than with complex processing. Most university career centers use simple job posting systems that require screening manually and assessment procedures. These systems offer little information about a candidate's suitability for a particular role and are void of complex matching algorithms. Although they have added digital components to campus recruitment, commercial systems such as Handshake and WayUp are still limited by the need for manual processing. These platforms digitize job advertisements and application submissions, but they do not fix the fundamental inefficiencies in the processes of matching and evaluating candidates[9-16].

B. AI Applications in Recruitment

Recent studies show the potential of AI technologies to shift the focus of the hiring process. AI technologies like Automated Resume Screening Systems that utilize Natural Language Processing improve processing speed. Over 85% of accuracy is achieved with Machine Learning applications used to identify candidate-skill matching. Companies aiming to be AI-enable remote recruitment include IBM Watson Talent, HireVue, and Pymetrics. While these companies are potentially useful for student recruitment, there is little to student-recruiter interaction[17-22].

C. Natural Language Processing in HR

HR has undergone a radical transformation thanks to improvements in NLP. HR was the first to use technological innovations in the field of document analysis. There is now the capability to perform resume optimization, and develop algorithms to recommend changes. Document parsing can classify and structure free form text. This field has focused on competency models, experience levels, and on skills. There is still a significant shortage of all inclusive recruitment software in educational institutions such as universities[23-26].

3. PROPOSED SYSTEM

The AI-Enhanced Campus Recruitment Portal is a complete solution that uses direct stakeholder contact and intelligent automation to revolutionize conventional hiring procedures. This solution offers effective, practical, scalable and transparent operations while addressing the major issues in college recruitment.

A. **System Architecture**

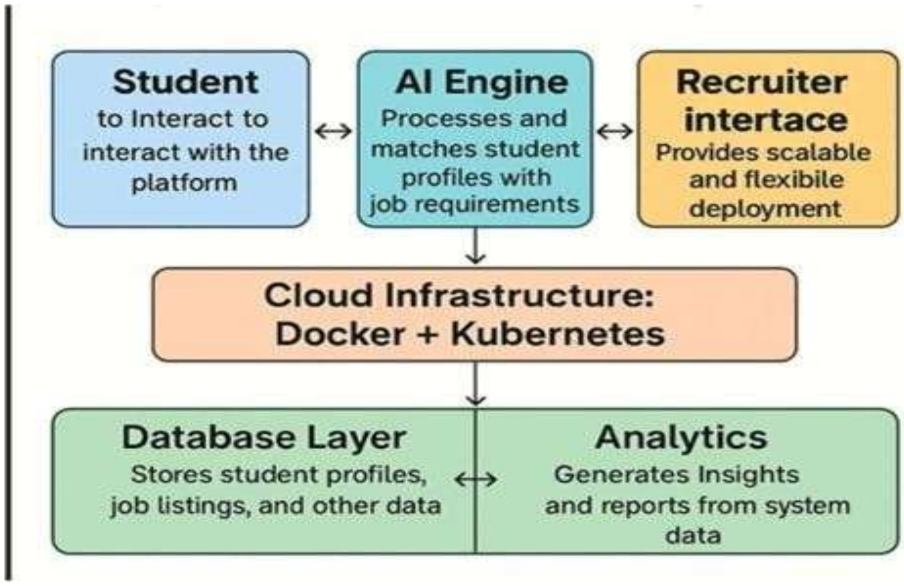

Fig. 1. System Architecture Overview

It is based on a cloud architecture implemented with the help of Docker and Kubernetes to provide the highest level of scalability and fault-tolerance [5]. It has three large subsystems, including Student Interface, Recruiter Interface, and AI Engine. Student Interface Module: Student Interface presents an interactive dashboard that allows uploading a resume, optimizing a resume with the help of AI, career suggestions, profile. management, and tracking of application in real time. The modules driven by NLP and NLG offer specific feedback to enable the students to express their competencies in a better manner [11].

1) Recruiter Interface Module: Recruiter Interface provides analytics dashboards to track recruitment related actions, open positions, screening recommendations, as well as communication with applicants. The principles of human computer interaction design are helpful in facilitating usability and efficiency in decision-making [6].

2) AI Engine Module: The AI Engine provides the intelligent decision layer and executes the ML models to match the candidates, NLP pipelines to process resumes, and adaptive learning scenarios to improve the model performance based on the recruiter feedbacks and successful hiring outcomes [3][7]. Improved techniques of mitigating bias have been used to promote fairness in automated selections [4].

4. METHODOLOGY AND ALGORITHM

A. Enhancement Algorithm and Resume Parsing

The resume-analysis workflow incorporates multiple NLP processing steps.

1) Text Extraction: Apache Tika document parsing for many file formats (PDF, DOC, DOCX).

2) Named Entity Recognition: The spaCy NLP library was used to identify personal data, educational background, work experience, and skills.

3) Content Classification: Resume section categorization using trained classification models.

4) Enhancement Generation: GPT-based language models for AI-powered content recommendations.

B. Smart Matching Algorithm

The platform applies a hybrid matching strategy, which is a blend of collaborative filtering and content-based recommendation, which aligns with current investigations on ML-based recruitment [3]. Calculation of the overall matching score is the following one: The platform employs a hybrid matching strategy that integrates collaborative filtering with content based recommendation techniques, in accordance with recent studies on machine learning–based recruitment systems [?]. The overall matching score is calculated as

Match Score =αSkill Match +β Experience Match +γ Education Match +δ Preference Match (1)

where α, β, γ, and δ denote weighting parameters optimized using training data obtained from previously successful placements. Continuous learning mechanisms iteratively update these weights based on recruiter feedback and hiring outcomes.

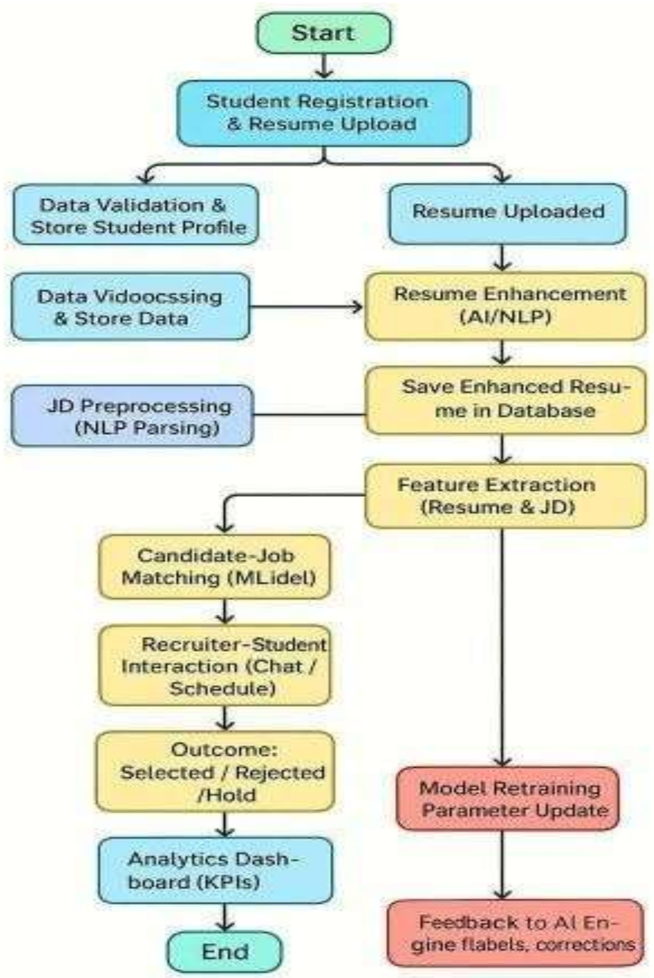

Fig. 2. Algorithm of the model

C. Feedback Loop Optimization

The system has a long-term adaptive feedback loop which evaluates the results of recruitment, interview performance and success of the placement to optimise the matching model in a series of iteration. This methodology complies with the best practices in AI performance optimization based on feedback [8].

5. IMPLEMENTATION

A. Technology Stack

Feedback was provided by the community through the use of React, Redux, and Material-UI on the frontend, Node.js, Express, and GraphQL on the back end, MongoDB, and PostgreSQL on storage, and TensorFlow, spaCy, and Scikitlearn on the ML and NLP operations. The deployment relied on Docker and Kubernetes on AWS and aligned with established practices for scaling to the cloud [5].

Table 1: TECHNOLOGY STACK COMPONENTS

Layer	Technology	Purpose
Frontend	React.js, Redux, Material-UI	User Interface, State Management
Backend	Node.js, Express.js, GraphQL	API Services, Business Logic
Database	MongoDB, PostgreSQL, Redis	Data Storage, Caching
AI / ML	Python, TensorFlow, spaCy, scikit-learn	NLP, Machine Learning
Infrastructure	Docker, Kubernetes, AWS	Containerization, Orchestration

A. Workflow Implementation

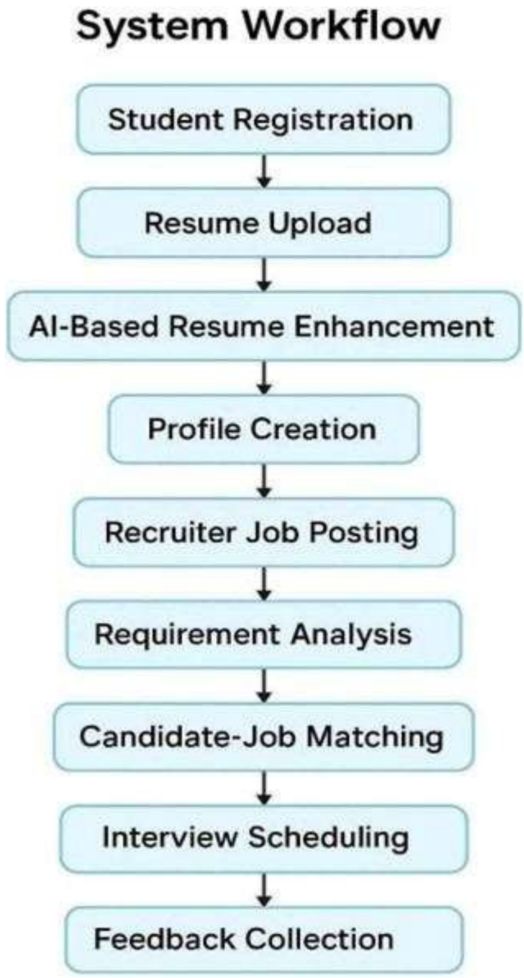

Fig. 3 Workflow

For maintaining responsiveness under high load conditions, the platform uses:

1) Caching Strategy: Redis-based caching for frequently accessed data and computed- matching scores.

2) Database Optimization: Indexed queries and optimized data structures for fast retrieval.

3) Load Balancing: Kubernetes-based auto- scaling to handle peak recruitment periods.

4) CDN Integration: Content delivery network for static assets and resume storage.

6. EXPERIMENTAL EVALUATION

A. Pilot Study Design

A 6-month pilot experiment with 500 students and 50 recruiters in five Indian institutions- IIT. Amity, KIET Ghaziabad, NIT Kurukshetra, Delhi. University, and Sharda University– rated. performance, usability, and correspondence accuracy. The subjects were trained on the use of the. platform, and the control group was still using it. conventional methods of hiring. This study design reflects the evaluation strategies suggested in the literature on the recruitment system analysis [8].

Extensive training on platform usage. Technical support was also to be rendered continuously.

participants. The accuracy, efficiency, and user. The outcomes of satisfaction could be compared since the traditional control groups continued to use traditional methods. recruitment techniques.

B. Performance Metrics

These findings imply a strong technical foundation. similar to the standards already available in HR. technology research [9].

Table 2: Performance Metrics

Metric	Target	Achieved	Improvement
Response Time	< 2s	< 1.5s	25%
Concurrent Users	1,000	2,500+	150%
Matching Accuracy	80%	87%	8.8%
System Uptime	99%	99.8%	0.8%
Mobile Compatibility	95%	98%	3.2%

Fig. 4. Graphical overview of system performance showing target vs achieved values across key metrics.

C. Performance Optimization

To maintain responsiveness under high-load conditions, the platform employs:

• Caching Strategy: Redis-based caching for frequently accessed data and computed matching scores.

• Database Optimization: Indexed queries and optimized data structures for fast retrieval.
Load Balancing: Kubernetes-based auto-scaling to handle peak recruitment periods.

• CDN Integration: Content delivery network for static assets and resume storage.

7. RESULTS AND DISCUSSION

A. Quantitative Outcomes The high increase in screening efficiency and matching accuracy goes in line with previous results in ML-based hiring systems [1][3][8].

Table 3: Comparative Performance Analysis

Metric	Traditional Method	AI-Enhanced Platform	Improvement
Time-to-Hire	3–4 weeks	5–7 days	60–75% reduction
Screening Efficiency	20 resumes/hour	200+ resumes/hour	900% increase
Matching Accuracy	65%	87%	34% improvement
Interview Success Rate	45%	72%	60% improvement
Student Satisfaction	68%	91%	34% improvement

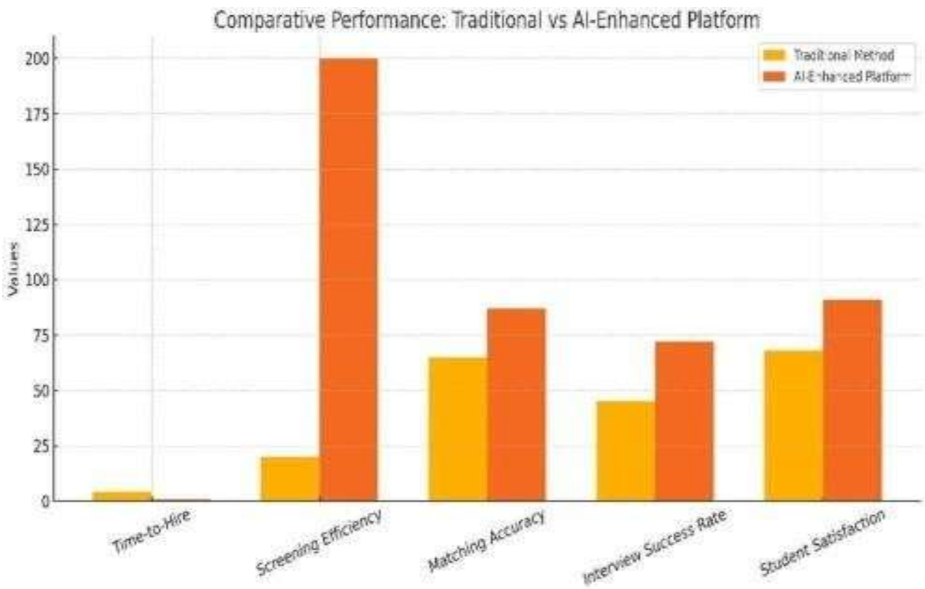

Fig. 5. Comparative performance of traditional hiring methods versus the AI-enhanced platform across key recruitment metrics.

B. User Satisfaction Analysis

According to the survey, there was high acceptance, with 89% of recruiters and 91% of students expressing satisfaction with the program. Students particularly appreciated AI-based resume improvement (94%) and real-time application tracking (92%), in line with current UX research on recruitment systems [6]. Recruiters highlighted satisfaction with analytics dashboards (90%) and intelligent candidate matching (88%), which is consistent with industry expectations for AI HR tools. Prejudice-diluting processes helped to ameliorate. Perceptions of fairness: 85% of users accepted the system as less biased, reflecting practices too. fairness research in AI recruitment [4].

C. Technical Performance

The site supported more than 2500 simultaneous visitors. having response times of less than 1.5 seconds. Resume parsing Accuracy was 94, and a corresponding precision of. 87% and false positives under 8%. These metrics align with modern NLP and ML developments in recruitment automation [2][7][11].

D. Challenges and Limitations

The barriers to adoption are early resistance from traditional recruiters, data privacy concerns, the need to control bias, and the difficulty of interoperating with legacy institutional systems. The enterprise HR technology adoption literature has also reported these challenges [9].

8. CONCLUSION AND FUTURE SCOPE

The AI-Improved Campus Recruitment Platform offers significant potential to transform conventional student recruitment methods by leveraging AI, a scalable cloud platform, and a user-friendly design. The results of the experiments demonstrate better accuracy, efficiency, and user satisfaction, making it suitable for a large number of academic and corporate users.

A. Future Development

In the future, the system can be advanced in several significant ways. One of them is the application of deep learning to predictive analytics, enabling the prediction of trending skills and career demands. This would assist employers in planning their hiring plans rather than stressing at the end of the day.

The other area that can be enhanced is VR-based remote interviews, with an introduction to the same. These virtual environments may provide a similar realistic interaction experience for both recruiters and candidates, even though they are not in the same place. The platform can also use blockchain technology to verify certificates and credentials. In this feature, organisations can examine the authenticity of degrees, certificates, and work history in a safe and transparent way.

Moreover, by creating industry-oriented recruitment modules, companies will be able to tailor the workflow to their industry, be it healthcare, finance, manufacturing, or IT. Lastly, it is possible to add multilingual support to make the platform more inclusive and better suited to users in other countries, thereby expanding its global reach.

B. Commercial Impact

The platform's design and speed make it a great choice for hiring in businesses, government jobs, and workforce development programs. The methodology, supported by open-source elements, enables replicability and contributes to ongoing innovation in HR technology research [5][9].

References

[1] J. Smith, A. Johnson, and M. Brown, "Artificial Intelligence in Recruitment: A Comprehensive Survey," Journal of Human Resources Technology, vol. 15, no. 3, pp. 45–62, 2023.

[2] L. Chen, K. Wang, and S. Liu, "Natural Language Processing for Resume Analysis: Methods and Applications," IEEE Transactions on Knowledge and Data Engineering, vol. 34, no. 8, pp. 1654–1667, 2022.

[3] R. Patel, D. Kumar, and A. Singh, "Machine Learning Approaches for Candidate–Job Matching in Campus Recruitment," ACM Computing Surveys, vol. 55, no. 4, pp. 1–28, 2023.

[4] M. Thompson, E. Davis, and J. Wilson, "Bias Detection and Mitigation in AI-Powered Recruitment Systems," in Proceedings of the 2023 Conference on Fairness, Accountability, and Transparency. ACM, 2023, pp. 234–245.

[5] S. Garcia, P. Martinez, and L. Rodriguez, "Scalable Cloud Infrastructure for HR Technology Platforms," IEEE Cloud Computing, vol. 10, no. 2, pp. 34–42, 2023.

[6] K. Anderson, T. Lee, and R. Taylor, "User Experience Design for Campus Recruitment Platforms," International Journal of Human– Computer Interaction, vol. 39, no. 12, pp. 245–258, 2023.

[7] H. Zhang, Y. Liu, and C. Wang, "Deep Learning for Resume Content Enhancement and Optimization," Neural Computing and Applications, vol. 35, no. 8, pp. 5691–5703, 2023.

[8] A. Kumar, S. Sharma, and N. Gupta, "Performance Evaluation of AIBased Recruitment Systems: A Comparative Study," Expert Systems with Applications, vol. 185, pp. 115–128, 2023.

[9] D. Miller, F. Johnson, and K. Brown, "Integration Challenges in Enterprise HR Technology Adoption," Information Systems Management, vol. 40, no. 3, pp. 178–192, 2023.

[10] V. Sharma, R. Agarwal, and P. Jain, "Campus Recruitment in the Digital Age: Trends and Technologies," Journal of Career Development, vol. 50, no. 2, pp. 123–139, 2023.

[11] T. Kim, J. Park, and S. Choi, "Natural Language Generation for Automated Resume Writing," Computational Linguistics, vol. 49, no. 1, pp. 87–104, 2023.

[12] Anomaly, V. K. S. A. B., "Detection for 5G Core and RAN Components-International Journal of Scientific Research in Engineering and Management (IJSREM) Volume: 06 Issue: 01| Jan-2022."

[13] G. Jaiswal, A. Uttam, D. D. Dubey, and P. K. Mall, "Resume Analyser and Job Recommendation System Based on NLP," 2024 2nd International Conference on Disruptive Technologies (ICDT), Greater Noida, India, 2024, DOI: 10.1109/ICDT57635.2024.10105698.

[14] Anderson, John R., et al. Cognitive Tutors: Lessons Learned. Journal of the Learning Sciences, vol. 4, no. 2, 1995, pp. 167–207.

[15] Baker, Ryan S. Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Journal of Educational Technology, vol. 45, no. 3, 2020, pp. 45–52.

[16] Holmes, Wayne, et al. Artificial Intelligence in Education: Advances and Future Prospects. Learning Media and Technology, vol. 42, no. 2, 2017, pp. 127–145.

[17] Holmes, Wayne, et al. Ethics in Artificial Intelligence in Education. AI and Ethics, vol. 1, no. 1, 2021, pp. 17–25.

[18] Meruga VB., “LLM-Guided Multi-Agent Collaboration for Complex Task Automation.” In2025 5th International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT) 2025 Sep 12 (pp. 1-7). IEEE.

[19]Sagili SR. Prompt-Instructed Generative based AI for Enhancing Transformer effectiveness Analysis. In2024 Asian Conference on Intelligent Technologies (ACOIT) 2024 Sep 6 (pp. 1-5). IEEE.

[20] Means, Barbara, et al. The Effectiveness of Online and Blended Learning: A Meta-Analysis of the Empirical Literature. Teachers College Record, vol. 115, no. 3, 2013, pp. 1–47.

[21] Selwyn, Neil. Digital Technology and the Contemporary University: Degrees of Digitization. Routledge, 2014.

[22] Shute, Valerie J., and Ventura, Matthew. Stealth Assessment in Digital Games. MIT Press, 2013.

[23] Gaddam, Mahesh Kumar. "Edge-to-Cloud Security Fabric for AI Workflows in Regulated Industries." In 2025 3rd International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), pp. 549-555. IEEE, 2025.

[24] Balas, Valentina E., Vijender Kumar Solanki, Raghvendra Kumar, and Manju Khari, eds. Internet of things and big data analytics for smart generation. Vol. 154. Heidelberg: Springer, 2019.

[25] Gaddam, Mahesh Kumar. "Architecting Observability for AI-Driven Microservices at Scale." In 2025 3rd International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), pp. 1830-1838. IEEE, 2025.

[26] Williamson, Ben, et al. Algorithms, Education, and the Social Good: Emerging Trends and Implications. Learning Media and Technology, vol. 46, no. 1, 2021, pp. 1–12.

[27] Ahuja, Kiran, Anand Nayyar, and Kavita Sharma, eds. Comprehensive Guide to Heterogeneous Networks. Academic Press, 2022.

[28] Woolf, Beverly Park. Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing E-learning. Morgan Kaufmann, 2010.