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AUTONIX: An AI-Driven Career Intelligence Platform for Resume Optimization and Interview Simulation

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Abstract: The contemporary job market has become increasingly complex, creating a powerful demand for smart systems that offer individualized career guidance. Common methods of career support are unsuccessful in adapting to personal requirements and rapidly changing skill needs. To address this challenge, this paper proposes AUTONIX, a modular career intelligence platform integrated with AI, aimed at providing scalable and flexible employability support.
The proposed system leverages Large Language Models (LLMs) to perform tasks including resume optimization, interview simulation, cover letter generation, and industry trend analysis. The platform is based on a full-stack architecture incorporating modern technologies such as Next.js for the frontend, Prisma ORM and NeonDB for data management, Clerk for secure authentication, and Inngest for asynchronous workflow processing.
Structured prompt engineering is a core feature of the system, ensuring that AI-generated outputs are context-aware, consistent, and aligned with user requirements. By utilizing the Gemini API, the system transforms unstructured inputs such as resumes and job descriptions into actionable and insightful information.
Experimental results demonstrate that AUTONIX produces high-quality, role-specific, and ATS-compatible outputs while maintaining system stability and responsiveness. The platform advances the application of AI-based career advisory systems and contributes to the development of scalable, intelligent, and real-world-deployable career guidance solutions.

Index Terms: Artificial Intelligence, Career Guidance System, Full-Stack Architecture, Large Language Models, Resume Optimization.

I. INTRODUCTION

The rapid development of technology and ongoing digital transformation has significantly altered the landscape of modern employment. Industries are dynamically evolving, requiring continuous shifts in skills and job roles. As a consequence, individuals are compelled to constantly upgrade their competencies and adapt their career plans to remain competitive in the job market.
Newcomers to the profession and students often face challenges in identifying the correct career path and aligning their skills with industry expectations. Conventional career advisory systems tend to be static, manual, and non-personalized, rendering them inadequate to address the diverse and dynamic needs of users.
Recent advances in Artificial Intelligence, particularly Large Language Models (LLMs), have introduced new opportunities for intelligent career guidance systems. These models can understand context, generate human-like text, and process unstructured data such as resumes and job descriptions. This enables the creation of systems that provide individualized recommendations, produce professional documents, and simulate interview scenarios.
Despite these advancements, deploying LLM-based applications at a production level remains a challenging task. It requires careful system design, including modular architecture, secure authentication, efficient data storage, and robust backend orchestration. Ensuring consistent and high-quality results from AI systems also demands well-defined prompt engineering strategies.
To overcome these challenges, this paper proposes AUTONIX, an AI-based modular platform that integrates multiple employability services into a single unified system. The platform is built using a layered architecture that ensures scalability, maintainability, and efficient integration of AI capabilities.
The significant contributions of this work are:

- Design of a scalable and modular AI-driven career advisory platform.
- Integration of multiple LLM-based employability tasks within a unified system.
- Introduction of structured prompt engineering for controlled and consistent output generation.
- Development of a system architecture suitable for realworld deployment.

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II. RELATED WORK

Early career recommendation systems primarily relied on rule-based and keyword-matching techniques [1]. These systems used predefined algorithms to map user profiles to job roles. While they performed effectively on structured datasets, they lacked flexibility and were unable to process unstructured data such as resumes and natural language queries.

With the advancement of Natural Language Processing (NLP), conversational agents were introduced to enhance user interaction [2]. These systems enabled users to access career guidance through chat-based interfaces. However, most of these approaches were limited by predefined templates and decision trees, restricting their ability to generate dynamic and personalized responses.

Subsequently, machine learning and deep learning techniques were incorporated to improve recommendation accuracy [3]. Methods such as collaborative filtering, classification algorithms, and reinforcement learning enabled more personalized job recommendations. Despite these improvements, such approaches were typically limited to specific tasks like job matching or skill recommendation and did not provide a comprehensive career assistance solution.

In recent years, Large Language Models (LLMs) have significantly transformed intelligent systems by enabling contextaware text generation, semantic understanding, and few-shot learning [4]. These capabilities make them suitable for complex tasks such as resume enhancement, interview preparation, and document generation.

Several modern applications have utilized LLMs for specific tasks such as resume screening or chatbot-based career assistance. However, these implementations are often limited to isolated functionalities and lack integration within a unified system architecture.

The AUTONIX platform addresses these limitations by introducing a comprehensive and modular framework that integrates multiple AI-driven services within a single platform. It emphasizes structured prompt engineering, scalable backend design, and seamless interaction between system components, thereby bridging the gap between research prototypes and realworld deployment.

III. SYSTEM ARCHITECTURE

AUTONIX follows a layered architecture to ensure scalability, modularity, and efficient integration of AI-driven components.

A. User Interface Layer

The user interface layer is responsible for capturing user inputs such as resumes, job descriptions, and interview re-

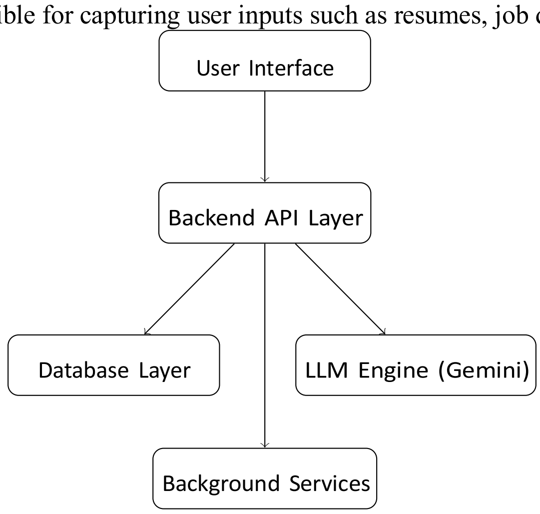

Fig. 1: Layered System Architecture of AUTONIX.

sponses. It provides an interactive environment that enables users to access different features of the platform seamlessly. This layer performs basic input validation and communicates with the backend through well-defined API endpoints. Additionally, it presents the processed outputs in a structured and user-friendly format, enhancing overall usability.

B. Backend and LLM Processing Layer

The backend layer acts as the central orchestration unit of the system. It manages key functionalities such as user authentication, session handling, request validation, and execution of application logic.

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A primary responsibility of this layer is to transform raw user input into structured prompts that can be effectively processed by the Gemini API. The LLM processes these prompts to generate context-aware outputs for tasks such as resume optimization, interview simulation, and content generation. The backend further refines and formats these responses before returning them to the user interface, ensuring consistency, accuracy, and reliability.

C. Data Storage and Background Services

The data storage layer is responsible for maintaining persistent records of user data, generated outputs, and interaction history. This supports efficient data retrieval and enables future personalization of results.
Background services handle asynchronous operations such as scheduled updates, analytics processing, and other nonblocking tasks. This design improves system responsiveness and prevents delays in user-facing operations.

D. Scalable Full-Stack Integration

AUTONIX integrates modern technologies to achieve scalability and performance. The frontend is implemented using Next.js, while Clerk is used for secure authentication and session management. Prisma ORM is used for database interaction along with NeonDB, a serverless PostgreSQL solution.
To efficiently handle time-intensive AI operations, Inngest is used for asynchronous workflow processing. This ensures that heavy tasks do not block the main application flow and allows the system to handle multiple user requests concurrently.

IV. AI WORKFLOW MODEL

The AI workflow in AUTONIX is designed to ensure structured, consistent, and context-aware processing of user inputs using LLMs. The system follows a step-by-step pipeline that transforms raw user input into meaningful and actionable outputs.
The workflow is formally expressed as:

$$O = f\big(P(U), C\big) \quad (1)$$

where U represents the user input, P denotes prompt structuring, C refers to contextual constraints, and f represents the LLM inference process.

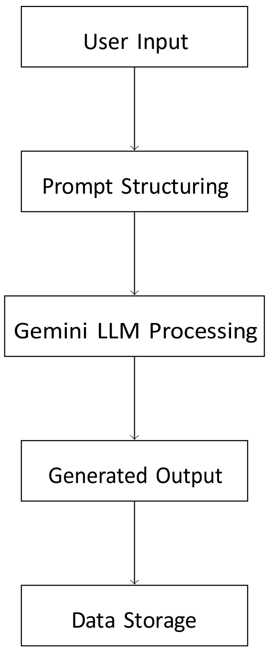

Fig. 2: AI Workflow Pipeline in AUTONIX.

A. Input Acquisition

The workflow begins with collecting user inputs such as resumes, job descriptions, or interview responses through the user interface. Since these inputs may be unstructured and vary in format, they are prepared for further processing.

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B. Prompt Structuring

The backend converts raw user input into a structured prompt by incorporating task-specific instructions and contextual constraints. This step plays a crucial role in guiding the LLM to produce accurate and relevant outputs while minimizing ambiguity.

C. LLM Processing

The structured prompt is passed to the Gemini API, where the LLM performs contextual understanding and generates appropriate responses. This includes tasks such as resume improvement, interview question generation, and content synthesis.

D. Output Processing and Storage

The generated output is further processed by the backend to ensure clarity, consistency, and proper formatting. The final result is stored in the database and presented to the user through the interface for future access and analysis.

V. METHODOLOGY

The methodology of AUTONIX focuses on integrating LLMs within a modular full-stack architecture to deliver intelligent and scalable career guidance. The system follows a pipeline-based approach where each stage processes and transforms unstructured user inputs into meaningful outputs.

A. Data Collection and Preprocessing

The process begins with collecting user inputs such as resumes, job descriptions, and interview responses. These inputs may vary in structure and format; therefore, preprocessing is applied to remove inconsistencies, clean noisy data, and standardize the format. This improves input quality and reduces ambiguity in further processing.

B. Structured Prompt Engineering

Structured prompt engineering is a core component of the system. Instead of passing raw input directly to the LLM, the system converts it into well-defined prompts by incorporating task-specific instructions and contextual constraints. This ensures that the generated responses are relevant, consistent, and aligned with user requirements.

C. LLM Inference and Output Generation

The structured prompt is sent to the Gemini API, where the LLM performs contextual understanding and generates outputs such as resume optimization suggestions, interview questions, and personalized feedback. The outputs are role-specific and actionable.

D. Post-processing and Output Formatting

The generated responses are further processed to ensure clarity, consistency, and professional formatting. This includes removing redundancy, structuring content, and aligning outputs with Applicant Tracking System (ATS) standards.

E. Asynchronous Processing

To ensure system responsiveness, asynchronous processing is used for handling time-intensive operations such as AI inference and analytics. Background services manage these operations without affecting user interaction.

F. Experimental Evaluation

To evaluate the effectiveness of AUTONIX, a set of resume samples was analyzed using an ATS. Initially, unoptimized resumes were evaluated against job descriptions to obtain baseline match scores. These resumes were then processed through AUTONIX, and the optimized versions were reevaluated using the same ATS.

Table I presents the baseline ATS match scores before optimization, and Table II presents the scores after processing through AUTONIX.

TABLE I: ATS Match Scores Before Optimization

Sample Resume	Match Score (%)
Sample 1	45
Sample 2	52
Sample 3	48

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Sample 4	50
Sample 5	46

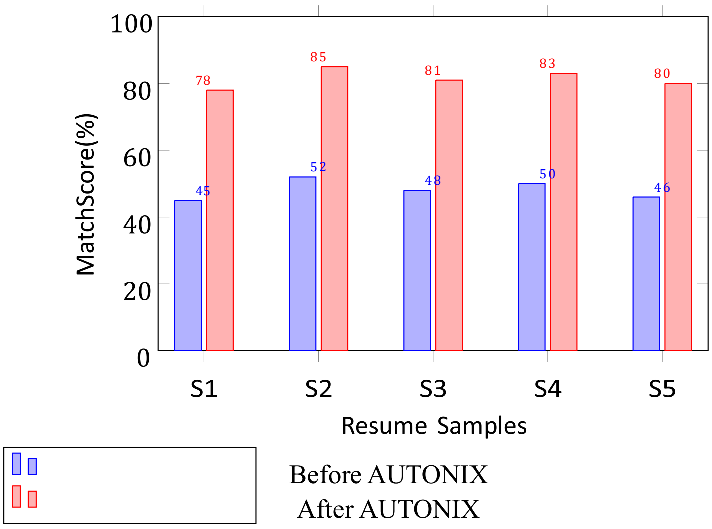
TABLE II: ATS Match Scores After Optimization

Sample Resume	Match Score (%)
Sample 1	78
Sample 2	85
Sample 3	81
Sample 4	83
Sample 5	80

G. Performance Comparison

Fig. V-G illustrates the improvement in ATS match scores before and after AUTONIX optimization across five resume samples. The results show a consistent and significant increase in match scores, with an average improvement of approximately 33 percentage points. Sample 2 recorded the highest post-optimization score of 85%, while Sample 1 showed the largest absolute gain, rising from 45% to 78%. These results confirm the effectiveness of structured prompt engineering in producing ATS-compatible, role-specific resume outputs.

ATS Score Improvement via AUTONIX



H. Discussion

The results clearly demonstrate that AUTONIX significantly improves resume quality and ATS match scores. The use of structured prompt engineering and AI-driven optimization enhances keyword selection, formatting, and readability.

The system consistently produces high-quality outputs across multiple samples, highlighting its effectiveness as an intelligent career assistance platform. Overall, the methodology ensures that the system remains reliable, scalable, and context-aware, making it suitable for real-world applications.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

This paper presented AUTONIX, a modular AI-integrated career intelligence platform developed to address the growing demand for personalized and scalable career guidance solutions. With the rapid evolution of industry requirements, traditional career assistance approaches often lack adaptability and contextual awareness. AUTONIX overcomes these limitations by integrating LLMs within a structured and production-ready full-stack architecture.

The platform combines multiple employability-oriented services, including resume optimization, interview simulation, cover letter generation, and industry analytics, into a unified system. The layered architectural design ensures clear separation of concerns and efficient communication between the user interface, backend services, and AI processing components.

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Additionally, structured prompt engineering improves the consistency, relevance, and quality of generated outputs by guiding the LLM with well-defined instructions and contextual constraints. The integration of asynchronous processing further enhances system performance by enabling non-blocking operations and efficient handling of multiple concurrent user requests.

Experimental observations indicate that the system is capable of generating coherent, role-specific, and high-quality outputs, thereby improving user preparedness for job applications and interviews. Overall, AUTONIX demonstrates the practical applicability of AI-driven solutions in the domain of career guidance and highlights the importance of combining advanced AI techniques with robust software engineering principles.

B. Future Work

While AUTONIX provides a strong foundation for AIbased career assistance, several opportunities exist for further enhancement. One direction is the integration of fine-tuned, domain-specific language models to improve output accuracy and reduce response variability.

Another important enhancement involves incorporating user behavior tracking and adaptive learning mechanisms. By analyzing user interactions over time, the system can deliver increasingly personalized recommendations and continuously refine its outputs based on user feedback.

Furthermore, integrating real-time job market data and analytics can enable the system to provide up-to-date insights on industry trends, in-demand skills, and emerging job roles. Additional improvements may include multilingual support to increase accessibility and voice-based interview simulation features for a more interactive experience. The inclusion of advanced evaluation metrics and feedback mechanisms can also strengthen system reliability and provide measurable performance insights.

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REFERENCES

[1] S. Kaur, R. Singh, and P. Sharma, "AI-Powered Personalized Career Guidance Systems Using NLP and Machine Learning," *IEEE Access*, vol. 9, pp. 112345–112356, 2021.

[2] Y. Zhang and H. Wang, "Conversational AI for Career Counseling Applications," *IEEE Trans. Learn. Technol.*, vol. 15, no. 3, pp. 245– 256, 2022.

[3] L. Chen, X. Liu, and M. Zhao, "Intelligent Job Recommendation Systems Using Deep Reinforcement Learning," *IEEE Trans. Artif. Intell.*, vol. 4, no. 2, pp. 123–135, 2023.

[4] T. Brown *et al.*, "Language Models are Few-Shot Learners," in *Proc.Adv. Neural Inf. Process. Syst. (NeurIPS)*, 2020.

[5] A. Zhang *et al.*, *Dive into Deep Learning*. MIT Press, 2021.

[6] D. Amodei *et al.*, "Concrete Problems in AI Safety," arXiv preprint arXiv:1606.06565, 2016.

[7] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in *Proc. NAACL*, 2019.

[8] A. Vaswani *et al.*, "Attention is All You Need," in *Proc. NeurIPS*, 2017. [9] K. Rajpurkar, R. Jia, and P. Liang, "Know What You Don't Know: Unanswerable Questions for SQuAD," in *Proc. ACL*, 2018.

[10] OpenAI, "GPT-4 Technical Report," arXiv preprint arXiv:2303.08774, 2023.

[11] Google, "Gemini: A Family of Highly Capable Multimodal Models," arXiv preprint arXiv:2312.11805, 2023.

[12] C. Manning, H. Schütze, *Foundations of Statistical Natural Language Processing*. MIT Press, 1999.

[13] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016.

[14] S. Bird, E. Klein, and E. Loper, *Natural Language Processing with Python*. O'Reilly Media, 2009.

[15] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*. MIT Press, 2018.

[16] P. Resnick and H. R. Varian, "Recommender Systems," *Communications of the ACM*, vol. 40, no. 3, pp. 56–58, 1997.

[17] X. Amatriain and J. Basilico, “Netflix Recommendations: Beyond the 5 Stars,” *Netflix Tech Blog*, 2015.
[18] M. Wooldridge, *An Introduction to MultiAgent Systems*. Wiley, 2009.