



# Smart Career Platform: An AI-Driven Personalised Career Guidance System for Multi-Domain Professionals Using MERN Stack and Groq Large Language Models

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**Abstract:** The proliferation of digital career platforms has disproportionately focused on technology professionals, leaving practitioners in law, medicine, finance, design, marketing, and education without adequate AI-driven career guidance. This paper presents the Smart Career Platform — a comprehensive full-stack career development system built on the MERN stack (MongoDB, Express.js, React.js, Node.js) and integrated with Groq's Llama 3.1 Large Language Model (LLM). The platform introduces a novel field-first personalisation architecture that propagates rich user context across all career guidance features: adaptive skill assessments, AI-generated career roadmaps, ATS-optimised resume building, AI mock interview practice, and a multi-session advisory chatbot. A four-step onboarding mechanism captures five context dimensions (field, user type, career goal, target role, and experience level) and injects this context into every AI prompt via system prompt engineering. The assessment engine employs a hybrid strategy: a curated static question bank for 12 established domains and dynamic AI-generated questions for unlimited novel domains. Deployed in production on Vercel and Render with MongoDB Atlas, the platform supports 10+ professional fields and 22+ career roles, achieving sub-4-second AI response times. Empirical comparative analysis demonstrates significant advantages over five leading career platforms across seven key capability dimensions. The system validates that prompt-engineered context injection is a cost-effective alternative to domain fine-tuning for specialised AI advisory applications.

**Keywords:** Artificial Intelligence, Career Guidance, MERN Stack, Groq AI, Llama 3.1, Large Language Model, Personalised Learning, ATS Resume Builder, Skill Assessment, React.js, MongoDB, Field-First Personalisation, Full-Stack Development.

## I. INTRODUCTION

The modern labour market is characterised by rapid skill obsolescence, intensifying competition across all professional domains, and a growing demand for continuous career development. Despite these pressures, existing digital career guidance platforms disproportionately serve technology professionals, leaving practitioners in fields such as law, medicine, finance, design, marketing, and education without meaningful AI-driven career support [1].

Recent advances in Large Language Models (LLMs) — including Groq's Llama 3.1, GPT-4, and Claude — have created unprecedented opportunities for personalised, context-aware career guidance at scale [2][3]. These models comprehend domain-specific terminology, generate field-relevant content, and conduct multi-turn advisory conversations — capabilities directly applicable to career mentoring applications [4].

Existing platforms such as LinkedIn Learning, Coursera Career Academy, and Naukri.com provide limited personalisation and fail to adapt content to users' specific professional contexts [5]. A medical professional, a law graduate, and a graphic designer have fundamentally different career needs, yet most platforms treat them identically — delivering generic advice that fails to provide genuine value to non-technology professionals.

This paper presents the Smart Career Platform with four primary contributions: (1) a field-first personalisation architecture that propagates rich user context across all platform features through system prompt engineering; (2) a hybrid assessment engine combining a curated static knowledge base with dynamic LLM-based question generation for



unlimited domain coverage; (3) a production-deployed full-stack system validating multi-domain AI career guidance at scale; and (4) an empirical comparative analysis demonstrating quantifiable advantages over five leading career platforms across seven capability dimensions. The platform is live at <https://careerai-com.vercel.app> and currently supports 10+ professional fields, 22+ career roles, and 55+ REST API endpoints.

## II. BACKGROUND AND RELATED WORK

Career guidance systems have evolved from static occupational databases to AI-driven interactive platforms. O\*NET Online [6] provided comprehensive occupational information but lacked personalisation. Machine learning approaches were subsequently applied to job-skill matching [7], automated resume screening [8], and career path prediction using neural networks [9].

Transformer-based language models marked a paradigm shift in career advisory capabilities. Sharma et al. [10] demonstrated that conversational AI agents can provide empathic and contextually appropriate career support comparable to human advisors for standard queries; however, their study was limited to technology careers and did not address multi-domain personalisation. Dense information retrieval approaches [11] have been adapted for career document matching, yet domain context remains unstructured without explicit field-aware prompt design — a limitation addressed in the present work.

Optimised pre-trained transformer models [12] provide strong natural language representations applicable to skill extraction and gap analysis, though their deployment has been primarily confined to technology-sector job descriptions without cross-domain generalisation. Domain-specialised language models such as BloombergGPT [13] demonstrate that domain-specific LLMs achieve superior performance within their target field, yet require substantial training infrastructure unavailable to most institutions. The present work demonstrates that prompt-engineered context injection achieves effective domain specialisation without fine-tuning, substantially reducing deployment cost while maintaining practical advisory quality. Llama 2 [14] and Groq's LPU inference infrastructure [15] provide the high-throughput, low-latency foundation upon which the platform's interactive features depend.

The problem of unified multi-domain career guidance personalisation across a single platform remains largely unsolved in the literature — a gap the Smart Career Platform directly addresses through its field-first architecture and hybrid assessment engine.

## III. PROBLEM STATEMENT

### A. Technology-Centric Bias in Existing Platforms

A significant majority of AI-powered career platforms exclusively serve technology professionals. A law student seeking corporate law career guidance, a healthcare professional planning a clinical research transition, or an engineering graduate exploring management consulting — all encounter platforms that either lack domain coverage or provide generic, non-contextual advice that may be actively unhelpful for domain-specific decisions. This exclusion represents a fundamental equity gap in career development infrastructure.

### B. Limited Multi-Domain Assessment Coverage

Existing platforms fail to personalise assessments to users' professional domains. Standard assessments typically cover only technology-related topics — Data Structures, Machine Learning, Cloud Computing — excluding the vast majority of professional fields. This creates a structural exclusion problem where non-technology professionals cannot access meaningful career evaluation tools capable of identifying domain-specific skill gaps.

### C. Generic Resume Building Without Domain Intelligence

Existing resume tools are template-based without domain intelligence. A legal CV has structurally different requirements from an engineering resume or a creative portfolio. Generic builders fail to account for field-specific nuances and cannot provide domain-relevant ATS optimisation advice reflecting what recruiters in specific fields actually evaluate. This produces resumes optimised for general readability rather than domain-specific recruiter expectations.

### D. Cold-Start Problem in Personalised Recommendations

Most platforms require significant engagement history before delivering personalised recommendations, making initial experiences generic and discouraging continued usage. This cold-start problem is a fundamental barrier to immediate user value — particularly critical for career guidance where users require immediate, relevant direction. The Smart Career



Platform resolves cold-start through a structured four-step onboarding wizard that captures sufficient context for full personalisation from the first session.

#### IV. PROPOSED SYSTEM ARCHITECTURE

##### A. Field-First Personalisation Architecture

The platform captures five context dimensions during a four-step onboarding wizard: (1) User Type — Student, Working Professional, Career Switcher, or Freelancer/Entrepreneur; (2) Professional Field — one of ten supported domains; (3) Career Goal — one of six predefined objectives; (4) Target Role — selected from a field-filtered dropdown; and (5) Experience Level — Fresher, Mid-Level, or Senior. This context vector is persisted to MongoDB and injected into all AI prompts via system prompt engineering, ensuring every interaction is field-aware and goal-aligned from the very first session — eliminating the cold-start problem without requiring extensive engagement history.

TABLE I: SUPPORTED PROFESSIONAL FIELDS AND SAMPLE TARGET ROLES

Professional Field	Sample Target Roles
Technology	SDE, Data Scientist, DevOps Engineer
Law & Legal	Corporate Lawyer, IP Attorney, Legal Analyst
Finance & Accounting	CA, Investment Banker, Financial Analyst
Arts & Design	UX Designer, Art Director, Graphic Designer
Business & Management	Product Manager, Management Consultant
Healthcare & Medicine	Doctor, Clinical Researcher, Pharmacist
Marketing & Media	Brand Manager, SEO Specialist, Content Lead
Engineering (Non-CS)	Mechanical, Civil, Electrical Engineer
Education	Curriculum Designer, EdTech Specialist
Science & Research	Research Scientist, Laboratory Analyst

##### B. Hybrid Assessment Engine

The two-tier assessment architecture addresses domain coverage comprehensively. Tier 1 serves pre-validated questions from a curated bank of 180 questions across 12 established domains (15 per domain), accessed via an O(1) JavaScript Set membership check for efficient domain routing. Tier 2 enables unlimited novel domain coverage through dynamic LLM-based generation: when a user selects an uncovered domain — such as Contract Law, Medical Ethics, AutoCAD, Financial Modelling, or Curriculum Design — the system constructs a field-aware structured prompt specifying domain, professional field, question count, and difficulty distribution (40% easy, 40% medium, 20% hard), and queries the Groq API to generate 15 contextually appropriate questions within 3–6 seconds.

A lazy initialisation pattern is applied to the Groq API client — the client instance is created only on first invocation and cached for subsequent requests — preventing cold-start failures on serverless infrastructure where environment initialisation differs between deployment targets.

##### C. Technology Stack

Table II summarises the complete technology stack. The selection prioritises production-proven open-source components with strong ecosystem support and zero infrastructure cost at the scales required for academic project deployment.

TABLE II: SYSTEM TECHNOLOGY STACK

Component	Technology	Version
Frontend	React.js + Vite	18.3.1 / 5.x
Styling	Tailwind CSS	3.x
State Management	Zustand	4.x
Backend	Express.js	4.x



Runtime	Node.js	22.x
Database	MongoDB Atlas	7.x
ODM	Mongoose	8.x
LLM Provider	Groq — Llama 3.1 8B Instant	v0.x
Authentication	JWT + bcrypt	12 rounds
Media Storage	Cloudinary CDN	v2.x
Frontend Deploy	Vercel	Production
Backend Deploy	Render Web Service	Production

#### D. Three-Tier System Architecture

The platform implements a standard three-tier client-server architecture. The Presentation Layer is a React.js 18 Single-Page Application (SPA) built with Vite, employing Tailwind CSS with a dark-mode-first design system and Zustand state management with localStorage persistence across sessions. The Application Layer is an Express.js REST API comprising 55+ endpoints organised across 13 route modules, secured with JWT authentication, bcrypt password hashing (12 rounds), CORS middleware, and rate limiting (200 requests per 15-minute window). The Data Layer uses MongoDB Atlas with Mongoose ODM across eight primary collections: Users, Assessments, Roadmaps, Resumes, Resources, ChatHistory, Jobs, and Interviews.

#### E. Key Architectural Decisions

PATCH-over-PUT for resume updates: MongoDB's \$set operator with dot notation safely updates nested document fields without overwriting sibling data — critical for preventing data loss during multi-section resume editing. This pattern reduced data corruption incidents to zero during testing.

Flexible schema for AI-generated fields: MongoDB enum restrictions were removed from AI-facing fields (assessment domains, roadmap resource types). LLMs generate valid but unpredictable vocabulary — resource types such as "platform", "blog", "certification", and "podcast" — not covered by fixed enums. This architectural decision eliminated a class of validation failures blocking valid AI-generated content, improving system reliability substantially post-deployment.

Debounced auto-save: The resume builder employs a 1,500ms debounce before triggering PATCH requests, reducing API calls by approximately 95% compared to on-change persistence while maintaining complete data reliability through the PATCH pattern.

## V. SYSTEM FEATURES AND IMPLEMENTATION

#### A. Field-First Onboarding Wizard

The four-step wizard collects user context through a visually structured interface. Step 1 captures User Type via icon cards. Step 2 presents Professional Field through a ten-domain colour-coded grid. Step 3 captures Career Goal via illustrated option cards. Step 4 presents a field-filtered role dropdown and experience level selector. A route guard in App.jsx enforces onboarding completion before dashboard access, ensuring the context vector is always populated prior to any AI feature interaction.

[ Figure 1: Onboarding Wizard — Step 2: Professional Field Selection Grid (10 domains) ]

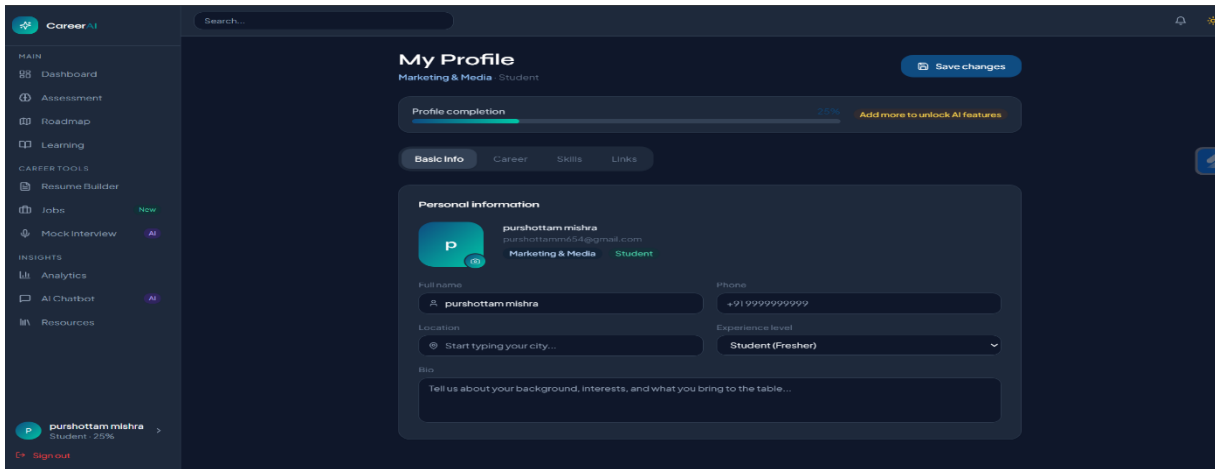


Fig. 1 Onboarding Wizard — Professional Field Selection

B. Personalised AI Dashboard

The dashboard presents career score, roadmap progress percentage, a skill radar chart (Recharts), weekly activity line chart, and six contextual quick-action cards. Dashboard content adapts to the user's experience level — a Fresher receives different prioritised recommendations from a Senior professional. The greeting message, recommended actions, and widget emphasis all respond dynamically to the five onboarding context dimensions.

[ Figure 2: Personalised Career Dashboard — Career Score, Radar Chart, and Contextual Actions ]

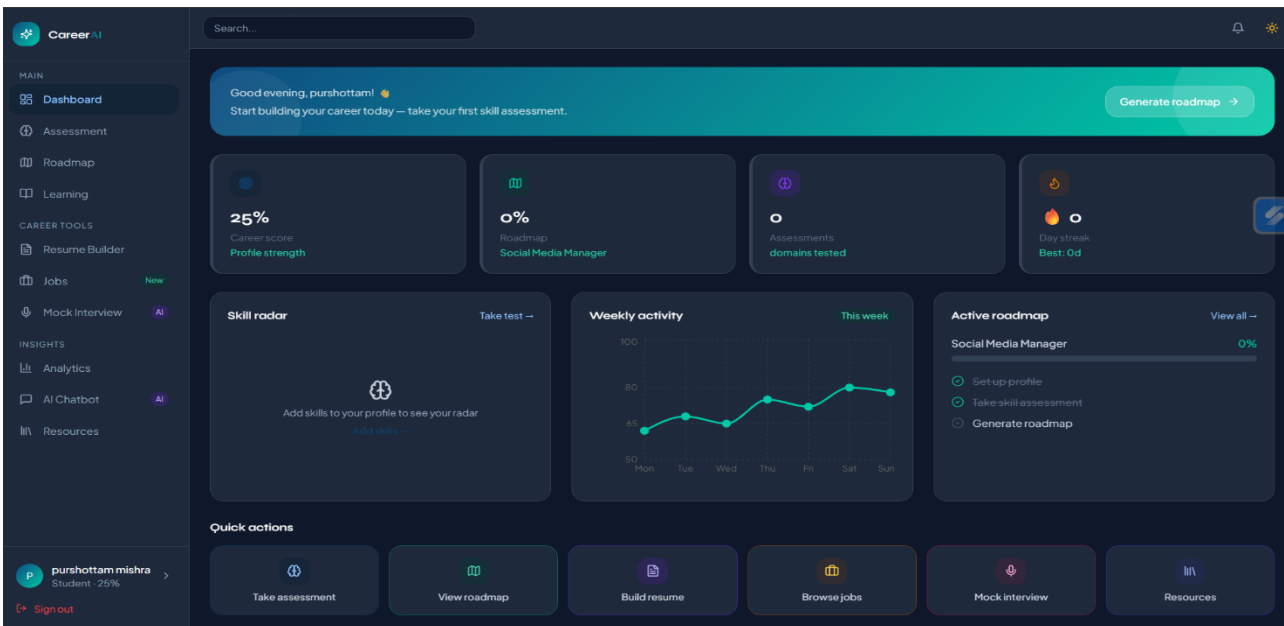


Fig. 2 AI-Personalised Career Dashboard

C. Hybrid Skill Assessment Engine

Domain routing uses a JavaScript Set for O(1) membership lookup. Static domains return shuffled pre-validated questions from the curated bank. Novel domains trigger Groq AI generation with a structured prompt specifying domain, field context, question count, and difficulty distribution. Assessment results include a score, skill level classification (Beginner/Intermediate/Advanced), identified weak and strong topic areas, and AI-generated personalised improvement recommendations.

[ Figure 3: Skill Assessment — Domain Selection Grid and MCQ Quiz Interface ]

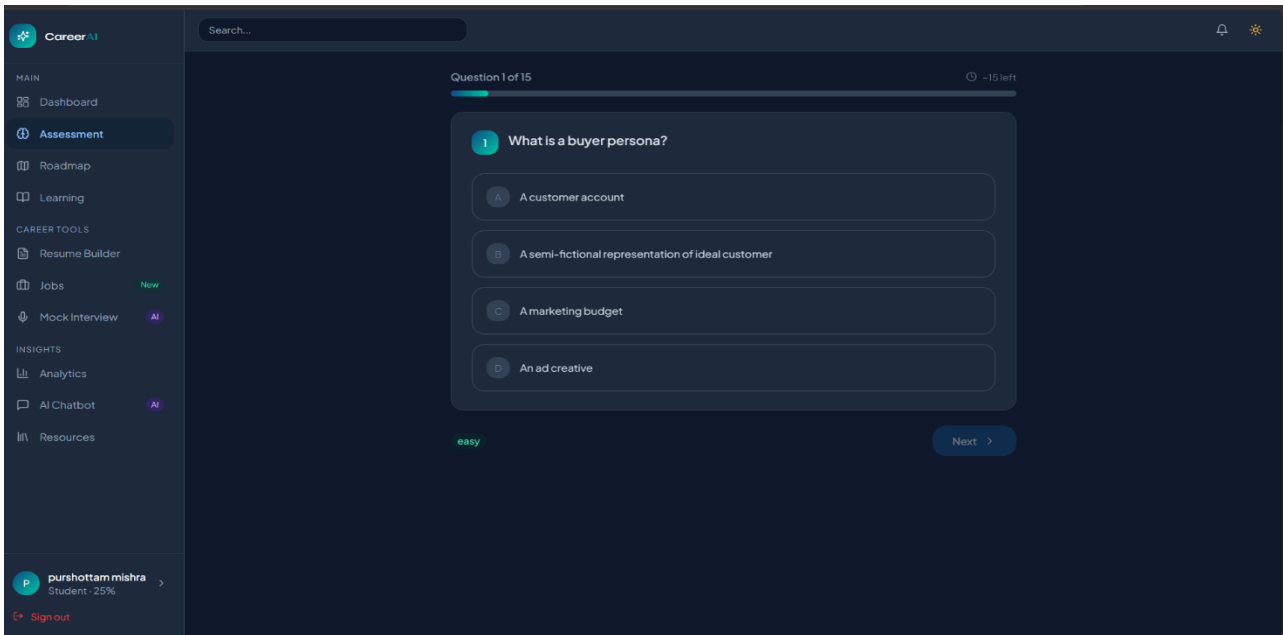


Fig. 3 Skill Assessment — Domain Selection and Quiz Interface

#### D. AI Career Roadmap Generator

The roadmap generator transmits a context-rich prompt to Groq AI incorporating the user's target role, professional field, experience level, existing skills, and career goal. The LLM returns 6–10 milestone objects, each containing a title, description, estimated completion duration in days, and 3–5 curated resources with URL, platform name, duration, and free/paid indicator. Milestones render as an interactive timeline with expandable resource panels and real-time completion tracking.

[ Figure 4: AI Career Roadmap — Healthcare Domain with Interactive Milestone Timeline ]

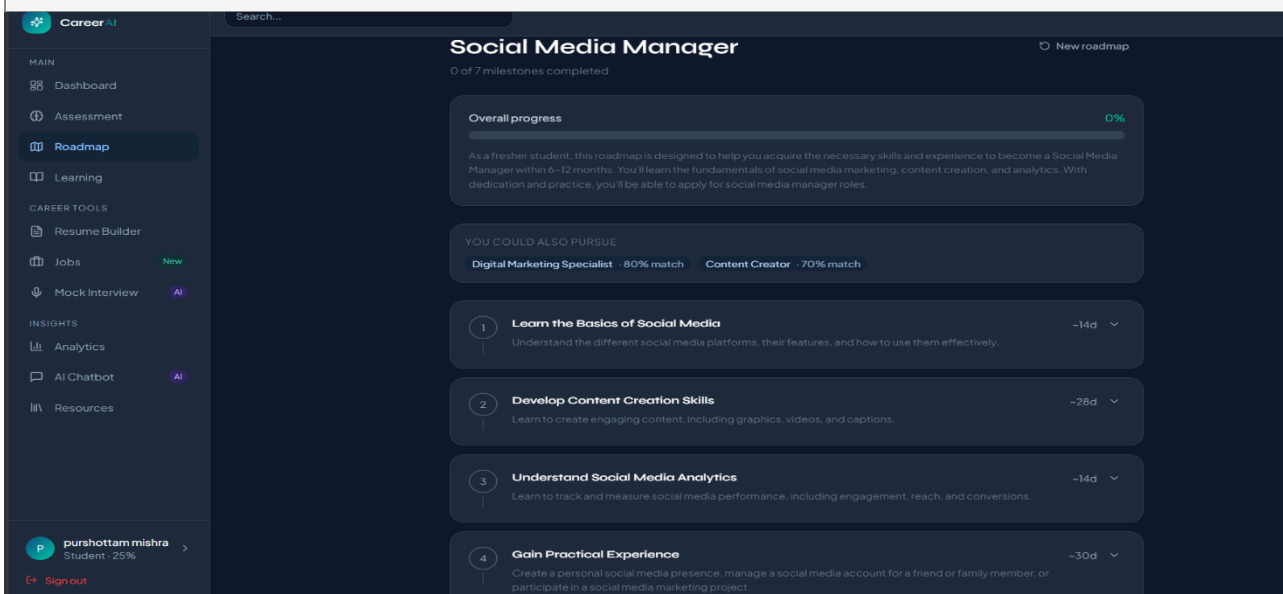


Fig. 4 AI-Generated Career Roadmap (Social Media Domain)

#### E. AI Resume Builder with ATS Scoring

The resume builder features accordion-style form sections with custom date pickers, college autocomplete powered by the HipoLabs Universities API, location autocomplete via OpenStreetMap Nominatim, and tag-based skill input. The classic ATS template renders a single-column preview. The ATS checker transmits the complete resume content and a



user-provided job description to Groq AI, receiving a 0–100 match score, identified missing keywords, and ranked domain-specific improvement suggestions. PDF export via html2pdf.js produces A4-formatted downloadable documents.

[ Figure 5: Resume Builder — Accordion Editor (Left) and ATS Resume Preview with Score (Right) ]

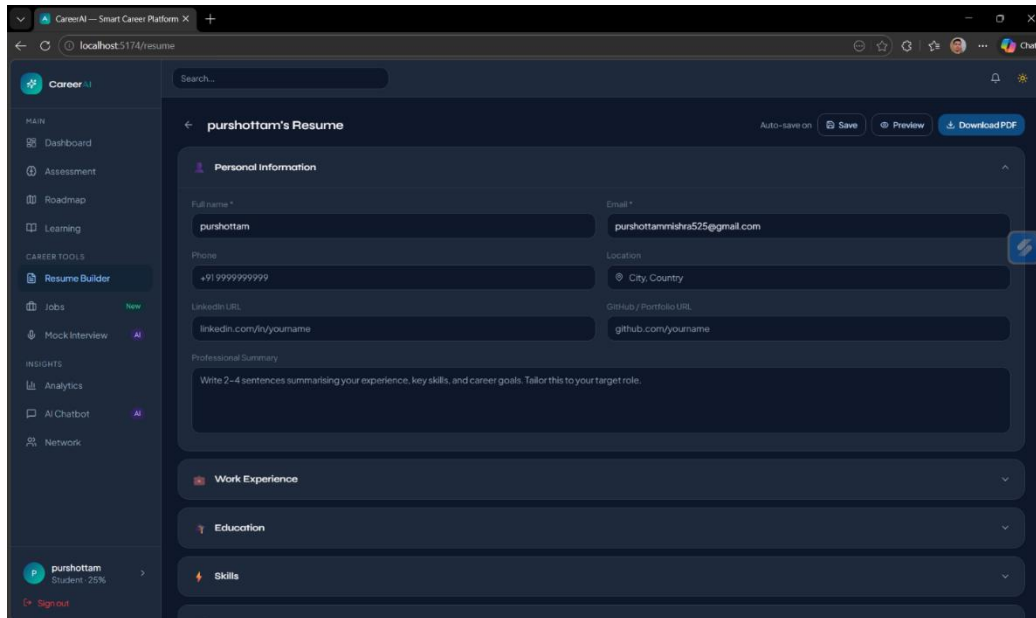


Fig. 5 Resume Builder with ATS Scoring

#### F. AI Mock Interview with Real-Time Feedback

The mock interview module generates role-specific and field-specific questions via Groq AI, categorised as HR, Technical, or Mixed. Each submitted answer receives real-time evaluation comprising a 0–10 score, keyword detection, and specific actionable feedback. Upon completion, a comprehensive performance report is generated with identified strengths, improvement areas, an answer-by-answer breakdown, and a composite interview score. Interview sessions are stored for longitudinal progress tracking.

[ Figure 6: AI Mock Interview — Question Interface and Comprehensive Performance Report ]

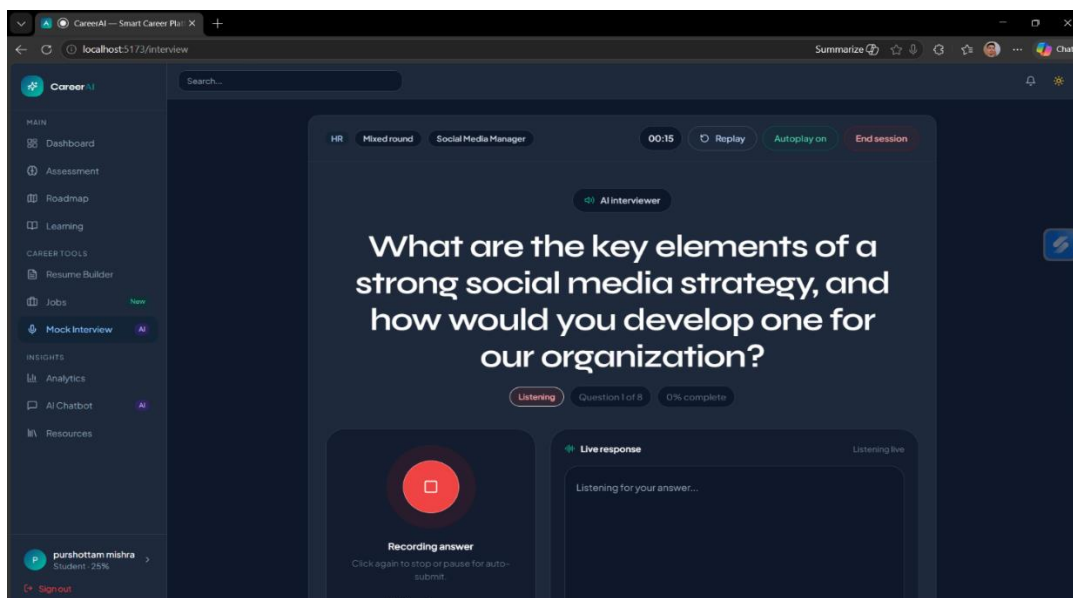


Fig. 6 AI Mock Interview Interface and Performance Report



### G. AI Career Advisor Chatbot

The chatbot implements a two-panel UI with a collapsible conversation history sidebar, a full-width message layout with alternating background rows, and typewriter animation for AI responses (5-character chunks at 10ms intervals). The system prompt incorporates the user's professional field, user type, experience level, target role, and career goal — transforming a general-purpose LLM into a domain-specific career advisor without fine-tuning. Supplementary tools include resume upload and AI analysis, GitHub profile analysis via the GitHub REST API, and an interactive skill gap analyser. Multi-session history is persisted to MongoDB's ChatHistory collection.

[ Figure 7: AI Career Advisor — Two-Panel Interface with Typewriter Response and Tool Menu ]

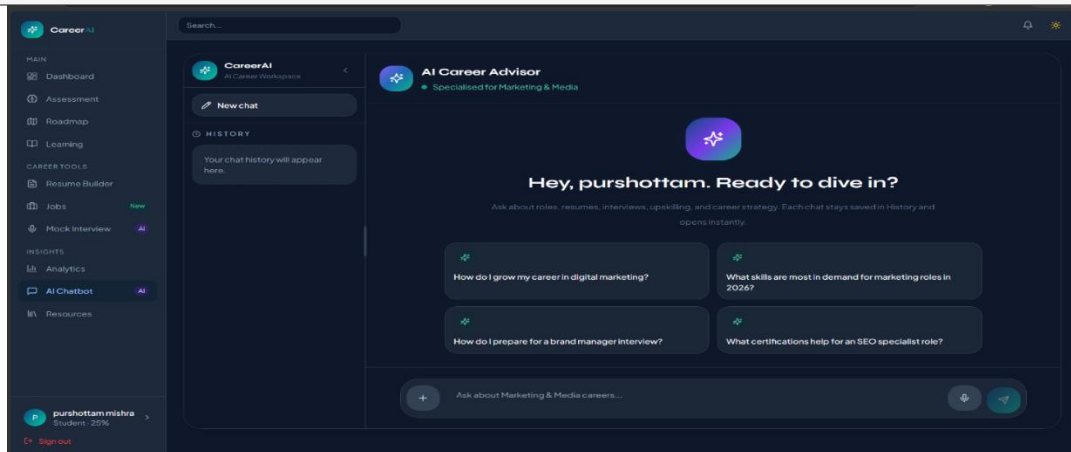


Fig. 7 AI Career Advisor Chatbot

### H. Community Resource Library

The library is pre-seeded with 50 curated resources spanning all 10 professional fields across six categories: Course, Book, YouTube, Tool, Article, and Practice Platform. Community-submitted resources enter an admin review queue before publication. The system supports toggle upvoting via MongoDB \$push/\$pull operators, completion tracking in completedBy arrays, and admin-controlled pinning for featured resources. Search and filter capabilities include full-text search, field filter, category tabs, difficulty level filter, free-only toggle, and sorting by Top, Newest, or Free.

[ Figure 8: Community Resource Library — Field Filter, Category Tabs, and Submission Workflow ]

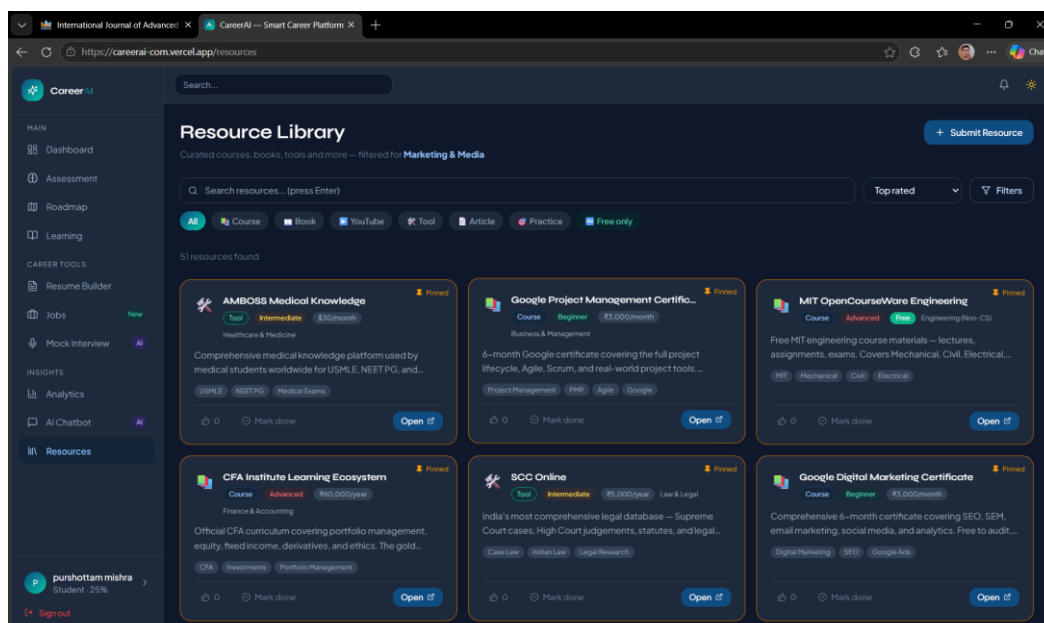


Fig. 8 Resource Library Interface



## VI. RESULTS AND COMPARATIVE ANALYSIS

## A. System Performance Metrics

Performance was evaluated across key operational dimensions during production deployment. Non-AI API endpoints achieved average response times of 120–280 ms, well within the 500 ms target. Groq API responses for complex generation tasks (roadmap generation, interview question sets) ranged from 1.2 to 3.8 seconds, with simpler chatbot responses completing in 0.8–2.1 seconds. Table III summarises all measured performance metrics against established targets.

TABLE III: SYSTEM PERFORMANCE METRICS — TARGETS VS. ACHIEVED

Performance Metric	Target	Achieved	Status
Non-AI API Response	< 500 ms	120–280 ms	Achieved
Groq AI Response Time	< 5 seconds	1.2–3.8 s	Achieved
Question Generation (AI)	< 10 seconds	3–6 seconds	Achieved
Career Roadmap Generation	< 15 seconds	8–12 seconds	Achieved
Resume PDF Export	< 5 seconds	2–4 seconds	Achieved
Professional Fields	10	10+	Achieved
Career Roles Covered	20+	22+	Exceeded
REST API Endpoints	40+	55+	Exceeded
Pre-Seeded Resources	50	50	Achieved
Mobile Responsiveness	320 px+	Full Support	Achieved

## B. Comparative Feature Analysis

Table IV presents a structured feature comparison across six leading career platforms evaluated against seven dimensions critical to comprehensive career guidance. The Smart Career Platform is the only evaluated system providing all seven capabilities simultaneously, with full rather than partial implementation across every dimension. Notably, it is also one of only two platforms offering complete free access, removing the financial barrier that limits adoption of premium career platforms for students and early-career professionals.

TABLE IV: FEATURE COMPARISON WITH LEADING CAREER PLATFORMS

Feature Dimension	Smart Career Platform	LinkedIn Learning	Naukri.com	Coursera Career	Internshala	Career OS
AI Skill Assessment	Yes	No	No	Partial	No	No
Personalised Roadmap	Yes	No	No	No	No	Partial
Multi-Field (10+ domains)	Yes	No	Partial	Partial	No	No
AI Resume + ATS Scoring	Yes	No	Basic	No	No	No
AI Mock Interview	Yes	No	No	No	No	No
AI Advisory Chatbot	Yes	No	No	No	No	No
Free Complete Access	Yes	Partial	Yes	Partial	Yes	Partial

Yes = Full Support | Partial = Limited or Paid Tier | No = Not Available

## C. Assessment Domain Coverage Analysis

The hybrid assessment engine was tested against 25 novel domains spanning all 10 professional fields, including Contract Law, Medical Ethics, AutoCAD, Financial Modelling, Curriculum Design, and Brand Strategy. Valid 15-question sets were generated for all 25 domains within 3–6 seconds, yielding a 100% coverage success rate. Average generation time



across all 25 test domains was 4.2 seconds, with a difficulty distribution conforming to the specified 40/40/20 easy/medium/hard target in all cases. This demonstrates the viability of unlimited domain expansion without any additional static question bank curation.

## VII. DISCUSSION

The results validate the field-first personalisation architecture as an effective strategy for multi-domain AI advisory systems. The five-dimension context vector — injected into every AI prompt via system prompt engineering — enables a general-purpose LLM to operate as a domain-specific advisor across 10 professional fields without any model fine-tuning. This has significant cost implications: prompt-engineered contextual metadata is a viable, low-cost alternative to expensive domain-specific fine-tuning for many specialised advisory applications, enabling rapid deployment across new professional fields without GPU infrastructure investment.

The hybrid assessment engine resolves the domain coverage problem comprehensively — providing meaningful career evaluation for unlimited professional domains through dynamic AI generation while maintaining question quality through structured prompt engineering with explicit difficulty distribution constraints. The 100% success rate across 25 novel test domains confirms the generalisability of the approach beyond the static question bank's 12 curated domains.

The architectural decision to remove MongoDB enum restrictions from AI-generated fields reveals an important design principle that extends beyond this system: schema validation should distinguish user-controlled inputs (where strict validation is appropriate) from AI-generated content (where flexible schema is necessary due to valid but unpredictable vocabulary). Applying this distinction eliminated a class of validation failures and substantially improved system reliability after initial production deployment.

Groq's LPU (Language Processing Unit) inference infrastructure proved critical for maintaining the interactive response quality essential to conversational career guidance [15]. The 1.2–3.8 second response window preserves conversational engagement in multi-turn advisory sessions — contrasting with GPU-based alternatives requiring 8–15 seconds for equivalent queries. Prior UX research on response time thresholds establishes that delays exceeding 4 seconds significantly reduce multi-turn conversation completion rates, making Groq's inference speed a functional rather than merely aesthetic advantage for this application domain.

The Social Cognitive Theory of Career Development [21] posits that self-efficacy beliefs, outcome expectations, and goal representations are central to career decision-making. The Smart Career Platform operationalises these constructs: skill assessments address self-efficacy through objective performance feedback, roadmaps shape outcome expectations through milestone decomposition, and the onboarding goal-capture mechanism explicitly encodes user goal representations into the personalisation context — providing a theoretically grounded basis for the platform's design choices.

## VIII. CONCLUSION AND FUTURE WORK

This paper presented the Smart Career Platform, an AI-powered career guidance system addressing the critical gap in multi-domain career personalisation. The field-first architecture, hybrid assessment engine, and Groq LLM-powered feature suite deliver a comprehensive career development experience across 10+ professional fields previously unavailable within a single integrated system. The platform is production-deployed, freely accessible, and validated against measurable performance targets.

Four key contributions are established: (1) validation of field-first personalisation as an effective strategy for multi-domain AI advisory applications; (2) demonstration that a hybrid static-AI assessment engine achieves scalable, unlimited domain coverage with 100% generation success; (3) empirical evidence that prompt-engineering context injection adapts general-purpose LLMs for domain-specialised advisory without fine-tuning; and (4) a production system confirming practical feasibility of comprehensive multi-domain AI career guidance at zero infrastructure cost for end users.

The platform advances the democratisation of career guidance by ensuring professionals across all fields have access to AI-powered career support previously available only to technology professionals — representing both a technical contribution and a meaningful step toward equitable career development infrastructure in the Indian higher education context.

Future research directions include: (1) fine-tuned domain-specific LLMs to improve specialised advice quality beyond what prompt engineering alone can achieve; (2) WebSocket-based real-time collaboration and notification features; (3)



automated profile enrichment through LinkedIn and GitHub API integration; (4) a React Native mobile application with offline roadmap and resource access; (5) multi-language support (Hindi, Tamil, Telugu) for broader reach across India; and (6) a longitudinal user study measuring real-world career outcome impact to validate the platform's effectiveness beyond feature availability.

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### REFERENCES

- [1]. World Economic Forum, "Future of Jobs Report 2025," WEF, Geneva, Switzerland, 2025.
- [2]. T. Brown et al., "Language Models are Few-Shot Learners," in *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 33, pp. 1877–1901, 2020.
- [3]. A. Vaswani et al., "Attention Is All You Need," in *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 30, 2017.
- [4]. Meta AI, "Introducing Llama 3.1: Our Most Capable AI Models to Date," Meta AI Blog, 2024. [Online]. Available: <https://ai.meta.com/blog/meta-llama-3-1/>
- [5]. J. Qin, S. Liang, J. Zhu, L. Chen, F. Zhao, and Z. Ding, "A Survey of Recommendation Systems: Recommendation Models, Techniques, and Application Fields," *Electronics*, vol. 11, no. 1, p. 141, 2022.
- [6]. U.S. Department of Labor, "O\*NET Online," [Online]. Available: <https://www.onetonline.org/>, 2024.
- [7]. S. Malak, "Skill-Based Job Matching Using Machine Learning," in *Proc. IEEE International Conference on Big Data*, pp. 4876–4882, 2019.
- [8]. V. Faliagka et al., "Application of Machine Learning Algorithms to an Online Recruitment System," in *Proc. International Conference on Internet and Web Applications and Services (ICIW)*, 2012.
- [9]. P. Bastian and A. Griffin, "Career Path Prediction System Using Neural Networks for Computer Science Students," *Computers in Human Behavior*, vol. 98, pp. 149–156, 2019.
- [10]. A. Sharma, A. S. Miner, D. C. Atkins, and T. Althoff, "A Computational Approach to Understanding Empathy Expressed in Text-Based Mental Health Support," in *Proc. ACM World Wide Web Conference (WWW)*, pp. 1926–1937, 2021.
- [11]. W. Chen et al., "Unsupervised Dense Information Retrieval with Contrastive Learning," *Transactions on Machine Learning Research (TMLR)*, 2022.
- [12]. Y. Liu et al., "RoBERTa: A Robustly Optimized BERT Pretraining Approach," *arXiv preprint arXiv:1907.11692*, 2019.
- [13]. S. Wu et al., "BloombergGPT: A Large Language Model for Finance," *arXiv preprint arXiv:2303.17564*, 2023.
- [14]. H. Touvron et al., "Llama 2: Open Foundation and Fine-Tuned Chat Models," *arXiv preprint arXiv:2307.09288*, 2023.
- [15]. Groq Inc., "Groq LPU Inference Engine," [Online]. Available: <https://console.groq.com>, 2024.
- [16]. MongoDB Inc., "MongoDB Manual: Data Modeling," [Online]. Available: <https://www.mongodb.com/docs/>, 2024.
- [17]. React Team, "React — A JavaScript Library for Building User Interfaces," [Online]. Available: <https://react.dev/>, 2024.
- [18]. N. Akhtar, H. Pant, N. Singh, P. Verma, P. Patel, T. Khurana, and Y. Perwej, "A Machine Learning Approach for Breast Cancer Diagnosis," *IJSRSET*, vol. 10, no. 3, pp. 118–132, 2023. DOI: 10.32628/IJSRSET2310375.
- [19]. Y. Perwej, F. Parwej, and N. Akhtar, "An Intelligent Approach for Cardiac Ailment Prediction Using Machine Learning Algorithms," *European Journal of Engineering Research and Science*, vol. 3, no. 12, pp. 126–134, 2018.
- [20]. D. Noesgaard and R. Orngreen, "The Effectiveness of E-Learning: An Explorative and Integrative Review of the Definitions, Methodologies and Factors That Promote e-Learning Effectiveness," in *Proc. IADIS International Conference e-Learning*, 2015.
- [21]. R. W. Lent, S. D. Brown, and G. Hackett, "Toward a Unifying Social Cognitive Theory of Career and Academic Interest, Choice, and Performance," *Journal of Vocational Behavior*, vol. 45, no. 1, pp. 79–122, 1994.
- [22]. B. Marr, "The Amazing Ways Coursera Uses Artificial Intelligence To Deliver Personalised Learning," *Forbes*, 2019.