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AI-Driven Career Feedback for Engineering Students: Enhancing Self-Regulated Learning and Professional Development

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1. Background

Engineering graduates enter the workforce possessing robust technical knowledge yet frequently encounter challenges in communicating their competencies and strategically positioning themselves for desired career trajectories [1], [2]. Research consistently demonstrates that employers prioritize skills extending beyond disciplinary expertise, including applied project experience, professional communication, leadership capacity, and evidence of continuous skill development [3], [4]. National survey data from the National Association of Colleges and Employers (NACE) reveals substantial perception gaps between employers and recent graduates regarding career-readiness competencies, with proficiency disparities exceeding 30 percentage points for leadership and professionalism domains [5]. For critical thinking and communication competencies, rated as essential by 99.5% of employers, only 55.2% of graduates demonstrate proficiency at levels employers consider adequate [6]. Within computing and software engineering disciplines specifically, recent graduates demonstrate notable challenges with configuration management systems, unit testing practices, and professional communication [7], indicating that technical curriculum alone insufficiently prepares students for industry expectations.

This gap between academic preparation and workplace readiness is further compounded by structural limitations within traditional career advising infrastructure [8], [9]. The median advisor-to-student ratio across higher education institutions reaches 296:1, with large research universities frequently exceeding 600:1 [10], [11]. Within engineering programs, academic advisors typically focus on curriculum compliance and graduation requirements, while dedicated career counseling remains resource constrained. Consequently, students often navigate critical career development decisions such as course selection aligned with target roles, project portfolio curation, technical certification priorities, and professional networking strategies with limited personalized guidance [12]. This advising bottleneck disproportionately affects students from underrepresented backgrounds who may lack familial or social capital to compensate for institutional resource constraints [3].

The proliferation of AI technologies presents new opportunities to democratize access to personalized career development support at scale [13], [14]. Commercial platforms such as VMock and Jobscan leverage machine learning algorithms to provide resume optimization feedback, while tools like LinkedIn Learning Coach utilize natural language processing to offer career pathway recommendations [15]. Research prototypes including CareerX and Career Compass demonstrate the feasibility of integrating resume analysis, skill gap identification, and learning roadmap generation into unified AI-driven systems [16]. However, existing implementations predominantly focus on surface-level document optimization or generic skill matching, without embedding career development within established learning frameworks that promote metacognitive awareness and student agency.

Career development as a self-regulated learning process requires students to actively direct their professional growth rather than passively receive guidance. Unlike declarative knowledge acquisition where students can succeed through instructor-led learning, career readiness demands that students independently identify goals, diagnose competency gaps, formulate development strategies, monitor progress, and adapt plans based on evolving industry requirements [17]. This fundamentally metacognitive process requiring awareness of one's thinking about professional development aligns directly with self-regulated learning theory. Traditional career advising, constrained by limited advisor capacity, cannot provide the sustained, personalized scaffolding necessary for developing these self-regulatory competencies.

Zimmerman's Self-regulated learning (SRL) theory provides a robust framework for conceptualizing career development as an intentional, metacognitive process [18], [19], [20]. This cyclic model includes three phases: (1) *forethought phase* where learners set specific goals and plan strategies to achieve them, (2) *performance phase* where they monitor their progress and adjust their approaches based on ongoing feedback, and (3) *reflection phase* where learners evaluate their outcomes and adapt future strategies accordingly [21], [22]. These processes directly apply to professional development, where students must identify target roles, assess their current competencies against industry standards, implement skill-building strategies, and continuously evaluate their readiness. While Engineering education research increasingly recognizes SRL as foundational to developing adaptive, lifelong learners capable of managing evolving technical and professional demands [17], practical implementations of SRL principles within career development interventions remain limited.

This study addresses this gap by developing and evaluating an AI-driven career feedback tool, ResuMatch Pro, specifically designed to operationalize SRL principles in career development. Overall, the purpose of the study is to investigate how AI-driven career feedback systems can operationalize self-regulated learning theory to support engineering students' professional development. Specifically, (1) RQ1: *To what extent does AI-driven career feedback enhance students' metacognitive awareness of their professional development needs, including recognition of competency gaps and understanding of development strategies?* (2) RQ2: *How do students perceive and utilize AI-generated feedback in their career planning and decision-making processes?* (3) RQ3: *What are the affordances and limitations of AI-based career feedback compared to traditional human advising?* These questions position the study within SRL theory while examining practical implementation challenges.

2. System Design and Features

The AI-driven career feedback tool called 'ResuMatch Pro' enables students to conduct comprehensive self-assessment, compare their profiles against specific job opportunities, and generate actionable career roadmaps aligned with desired timelines. It comprises three integrated features or workflows that leverage natural language processing and competency-based analysis to provide personalized feedback. Appendix A includes screenshots of the tool interface for reference. The tool is designed to operationalize the SRL framework - In the *forethought phase*, the tool helps students set specific, realistic career goals by comparing their profiles against actual job requirements and surfacing previously unconsidered pathways. In the *performance phase*, it provides milestone-based roadmaps that enable students to monitor progress, identify when strategies require adjustment, and maintain developmental momentum through concrete checkpoints. In the *reflection phase*, the tool prompts metacognitive awareness by explicitly identifying competency gaps, explaining why specific skills matter for target roles, and encouraging students to evaluate whether their development strategies align with their evolving goals. This explicit, structured approach addresses a documented challenge: students often possess relevant competencies but lack the metacognitive awareness to recognize their significance or articulate them effectively to employers.

2.1 Workflows within ResuMatch Pro

Workflow 1: Resume Analysis. Upon creating an account, students upload their current resume for comprehensive analysis. The tool evaluates the resume across multiple dimensions like completeness, content quality, formatting, and generates an overall completeness score (0-100%) alongside section-specific scores (1-5) for major sections. The system provides a summary of key strengths and improvement areas, followed by a detailed list of recommendations. For example, the tool might identify that a student's resume is missing a summary section or suggest quantifying project impacts with measurable outcomes. This feature supports the reflection phase of SRL by requiring students to systematically evaluate their current professional identity against objective rubrics and receive immediate feedback on their self-presentation.

Workflow 2: Job Match Analysis. This feature allows students to assess their readiness for specific employment opportunities. Students either upload a job description or search for positions by job title and location. The tool then conducts a detailed comparison between the student's resume and the job requirements, identifying matching qualifications, missing competencies, and development priorities. The analysis produces a match percentage and an explicit readiness recommendation, indicating whether the student should apply immediately, develop specific skills before applying, or consider the role as a longer-term target. When gaps are detected, the tool prompts students with targeted questions to surface potentially overlooked experiences. For instance, if communication skills appear absent from the resume, the system asks about presentation experiences, technical writing, or team collaboration contexts that students may not have initially documented. This interactive gap-filling process helps students recognize transferable skills and experiences they possess but have not effectively articulated. This workflow supports the forethought phase of SRL by forcing students to articulate specific career targets and identify matching qualifications as well as by helping students set realistic goals and make strategic decisions about job applications. Rather than encouraging indiscriminate application to numerous positions, the tool promotes intentional targeting of opportunities aligned with current competencies while identifying specific development needs for aspirational roles.

Workflow 3: Career Roadmap Analysis. This feature serves as the core intervention for long-term professional development planning. Students specify a target job title, desired company, preferred location, and timeline for achieving this goal (e.g., 1 year, 3 years from present). The system generates a comprehensive Individual Development Plan (IDP) structured around five components: current gaps, skills to acquire, action plan with timeline, recommended resources, and milestones. The current gaps analysis identifies specific competency deficiencies relative to the target role while skills to acquire section translates these gaps into learning objectives, such as mastering particular programming frameworks or gaining experience with agile project management methodologies. The action plan provides a timeline-aligned sequence of developmental activities. For a 3-year roadmap, the plan might structure recommendations across near-term (0-12 months), intermediate (12-24 months), and advanced (24-36 months) phases, ensuring progressive skill building and realistic pacing. Recommended resources include specific online reading material, courses, suggested project types, and professional development opportunities such as technical leadership roles or conference presentations. Finally, milestones establish checkpoints for self-monitoring progress, such as completing foundational coursework by month 6 or finishing a capstone project by month 18. These milestones operationalize the performance phase of SRL by providing concrete benchmarks against which students can monitor their developmental trajectory and adjust strategies as needed. The Career Roadmap workflow synthesizes forethought (goal specification, strategic planning), performance (milestone tracking, resource engagement), and self-reflection (gap awareness, progress evaluation) components of SRL into a unified, personalized development framework. By requiring students to articulate specific career targets and timelines, the tool encourages intentional forward-looking professional identity formation rather than reactive career navigation.

2.2 Technical Implementation

The system utilizes large language models to analyze resume content, job descriptions, and industry competency frameworks. The AI model is prompted to evaluate resumes against predefined rubrics aligned with National Association of Colleges and Employers (NACE) career readiness competencies and domain-specific technical standards for engineering and computing roles. Personalization is achieved through dynamic prompt engineering that incorporates the student's specified career targets, current profile, and timeline constraints into feedback generation. The system maintains a database of industry-standard competency expectations for common engineering and computing roles, enabling context-appropriate recommendations across diverse career paths including software engineering, data science, systems engineering, product management, and other technical positions.

3. Methods

The mixed-methods study employed a pre-post intervention design where students completed a baseline (pre-activity) survey, interacted with the tool and then completed a post-activity survey.

3.1 Context and Participants

The study was conducted in Fall 2025 and involved 24 students enrolled in computing and related engineering programs at a large Midwestern research university. Participants were recruited through email announcements distributed via departmental listservs. Participation was voluntary, students provided informed consent and received no course credit or monetary compensation. The sample comprised 17 graduate students and 7 undergraduate students in their junior or senior years. Professional work experience ranged from 0 months to 3 years, including full-time employment, internships, and research assistantships. This variation in experience levels provided a diverse sample representing different stages of career development and varying levels of existing professional preparedness.

Students were instructed to first complete a pre-activity survey assessing self-regulated learning competencies related to career planning. Following the pre-activity survey, students received a link to YouTube instructional video demonstrating features and workflows of the tool. Students were asked to: (1) upload their current resume for comprehensive analysis, (2) conduct at least one job match analysis using either a specific job posting or a search for positions matching their interests, (3) generate a career roadmap by specifying a target role, organization, and desired timeline and (4) review all feedback carefully. Upon completing their interaction with the tool, participants were prompted to complete a post completion survey.

3.2 Data Collection

Data was collected using pre- and post- surveys administered by Qualtrics. The pre-activity survey measured goal clarity, gap awareness, strategic planning capacity, and self-efficacy using 5-point Likert scale items (1 = Strongly Disagree, 5 = Strongly Agree). Demographic information including academic standing, major, and professional work experience was also collected. Refer to Appendix B for the pre-activity survey questions. The post-activity survey included Likert scale and open-ended questions to assess (1) perceptions of tool quality like relevance, accuracy, scaffolding quality, and actionability of recommendations and (2) changes in metacognitive awareness, strategic planning intentions, ownership of professional development, and career trajectory. Refer to Appendix C for the post-activity survey questions.

3.3 Data Analysis

Quantitative data from pre- and post- activity surveys were analyzed using descriptive statistics to assess changes in self-regulated learning competencies. Qualitative responses to open-ended prompts were analyzed using thematic coding procedures. Two researchers independently reviewed all responses and developed an initial codebook through open coding, identifying emergent themes related to gap awareness, developmental strategies, and perceived tool value. Codes were then organized into thematic categories aligned with the research questions. Discrepancies in coding were resolved through discussion until consensus was achieved. Representative quotes were selected to illustrate key themes in the Results section.

4. Results

The mixed-methods analysis revealed four key themes characterizing students' experiences with the AI-driven career feedback system.

Theme 1: From Vague Aspirations to Explicit Competency Awareness
Pre-survey data revealed substantial variability in students' initial self-regulated learning competencies. Only 37.5% (n=9) could name a specific target job title and company (Appendix D1, Q2_1), 29.2% (n=7) felt confident listing missing skills (Q2_2), and just 16.7% (n=4) reported having a written development plan (Q2_3). Following system interaction, students demonstrated substantial gains in metacognitive awareness. Critically, this awareness extended beyond simply knowing what employers want to - reflecting on their own thinking and planning processes. While 91.7% (n=22) reported increased understanding of competency dimensions employers seek (Appendix D3, Q2_1; $M = 4.42$, $SD = 0.58$).

Analysis of identified surprising gaps and helpful recommendations by the tool revealed how this awareness developed. More than half of students (Appendix D4, 66.7%, n=16) found they had relevant experiences but failed to express them effectively. One student mentioned a recommendation they would follow, "*Quantify more achievements in each role. Instead of just stating tasks, focus on the impact you made with numbers and metrics. For example, instead of 'Developed reports using SAS', try 'Developed and automated SAS reports that reduced reporting time by 40% and improved data accuracy by 15%'*." Another noted: *"Nothing too surprising, I already knew about the skill gaps that exist. I was surprised it mentioned Data Analysis as well, but I now know I need to more explicitly state about it there."* These responses demonstrate metacognitive reflection as students are not merely learning new information but evaluating how they think about and represent their competencies. The student recognizing they possessed data analysis skills but failed to articulate them exemplifies self-regulated monitoring as they evaluate the gap between internal knowledge and external presentation and then plan strategic adjustments. About 37.5%, (n=9) discovered gaps in specific technical skills or certifications (Appendix D5). Additionally, 20.8% (n=5) (Appendix D4) expressed surprise at deficiencies in soft skills and professional competencies, particularly leadership and communication.

Theme 2: Specificity and Actionability of AI-Generated Feedback

Students rated the tool highly across all quality dimensions (Appendix D2), with relevance (M = 4.38, SD = 0.65), accuracy (M = 4.29, SD = 0.69), scaffolding (M = 4.25, SD = 0.74), and actionability receiving particularly strong ratings (M = 4.46, SD = 0.59), with 91.7% (n=22) indicating recommendations were specific enough to act upon immediately. Students' planned actions demonstrated this translation from awareness to strategy. Technical certifications represented the most common commitment (37.5%, n=9), including AWS and Google Cloud credentials. Specific coursework constituted 29.2% (n=7), project-based learning 20.8% (n=5), and professional development activities 12.5% (n=3) (Appendix D5). Over half of respondents (Appendix D6, 54.2%, n=13) emphasized specificity and personalization as the primary distinguishing feature. One student stated: *"It's faster, detailed and specific. I like the actionable items it returns to guide us in fulfilling the requirements."* Another explained their planned action: *"Deploying a ML model using AWS"*, demonstrating integration of technical skill development with applied project experience.

Theme 3: Increased Ownership and Strategic Planning

Post-intervention measures demonstrated substantial shifts toward proactive professional development management (Appendix D3). Career trajectory clarity received the strongest response, with 95.8% (n=23) reporting clearer understanding of their professional path (Q2_4; M = 4.50, SD = 0.51). Students reported increased ownership of professional development, with 91.7% (n=22) feeling more equipped to manage their own growth (Q2_3; M = 4.38, SD = 0.58), and 87.5% (n=21) intending to modify future course or project choices (Q2_2; M = 4.33, SD = 0.64). The shift from baseline to post-intervention is striking. Fewer than one in five students had a written development plan initially (16.7%), yet nearly nine in ten reported intentions to modify their decisions following the intervention (87.5%). One student captured this proactive stance, *"...it was a great reminder that I should focus on networking, work on personal projects, attend information sessions and company events."* This quote reveals a shift in self-regulatory behavior such that the student is now actively planning and prioritizing multiple developmental strategies rather than waiting for opportunities to present themselves. Other students demonstrated strategic planning by mentioning that they will *"Contribute to open source projects"* and *"Proactively seek mentorship from experienced TPMs"*

Theme 4: AI as Scalable Complement to Human Advising

Students demonstrated sophisticated understanding of the AI tool's role within broader career development infrastructure. 41.7% of the students (n=10) emphasized accessibility and immediacy as key advantages (Appendix D6). One stated simply, *"Was not sure who to get* *feedback from on resume. This is great!*" This addresses a documented challenge with advisor-to-student ratios exceeding 296:1. Another observed, *"Quick and detailed. I can see it being useful for younger students who are building their first resume. Online research can be very overwhelming."*. However, 33.4% students (n=8) acknowledged limitations while noting value. One student noted, *"I am rewriting my resume so it was helpful to get quick feedback with examples. It definitely makes it very easy. Overall, it is good snapshot of things that someone might have missed, although some points are vague. AI system suggested to include summary statement but a human would have realised that if I included summary it would bleed to next page."* Other students mentioned, "*Some of the things the tool pointed out were incorrect"* and *"it incorrectly claimed there is no phone number"*. This shows that the technology still has gaps and needs to be used with critical oversight. These reflections reveal students view AI career feedback as occupying a distinct niche - excelling at immediate, structured baseline assessment while human advisors offer contextual judgment for complex decisions.

5. Discussion and Implications

5.1 Discussion

This study examined the efficacy of an AI-driven career feedback system in enhancing engineering students' self-regulated learning competencies related to professional development. Results demonstrate that personalized AI-generated guidance significantly improved students' metacognitive awareness, provided actionable recommendations, and fostered ownership of professional growth.

The substantial improvement in metacognitive awareness, with over 90% reporting increased understanding of employer expectations, directly supports the premise of SRL that effective self-regulation begins with accurate self-assessment. Baseline data revealed a critical disconnect: while most students articulated career aspirations, fewer than one-third could identify developmental gaps, and less than one-fifth possessed strategic plans. This represents a fundamental vulnerability in the forethought phase of self-regulated learning. The AI system addressed this by providing structured multidimensional feedback across technical expertise, applied experience, leadership, and communication dimensions. This operationalized previously vague career advice into concrete, actionable categories. The high ratings for actionability ($M = 4.46$) and trajectory clarity ($M = 4.50$) suggest the system successfully bridged the performance phase by translating gap awareness into specific developmental strategies.

The qualitative data provide additional important context. Many students possessed relevant competencies but lacked vocabulary to recognize their significance. The tool's emphasis on 'competency dimensions' helped students reinterpret experiences through an employer-centric lens. Additionally, the interactive gap-filling features surfaced latent evidence students had not self-identified, addressing a common challenge where students underreport experiences they do not perceive as ‘professional’. Students’ reflections reveal AI feedback occupies a distinct niche in career support. Human advisors provide relational support and contextual nuance AI cannot replicate. Generic online resources offer breadth without personalization. The AI tool provided immediate, specific, comprehensive feedback at a level of detail students found difficult to access through existing channels, suggesting its value is augmentation rather than replacement.

5.2 Theoretical Implications

This study demonstrates how AI systems can operationalize SRL frameworks at scale. Traditional SRL interventions require significant instructor facilitation and struggle with personalization. The scale dimension is particularly critical given documented advising ratios exceeding 296:1 and resource constraints that prevent personalized SRL support for most students. AI-driven feedback provides immediate individualized scaffolding while maintaining theoretical fidelity to SRL principles. Effective AI scaffolds must integrate all three SRL phases. Tools focusing solely on gap identification without strategic planning leave students aware of deficiencies but uncertain how to address them. Tools providing generic action plans without personalized analysis fail to engage metacognitive awareness. The integration of goal specification, competency analysis, and timeline-aligned planning represents theoretically coherent AI-mediated self-regulated learning. The study also highlights the importance of actionability [23]. High metacognitive awareness without clear pathways risks inducing anxiety. The strong actionability ratings and diversity of planned activities suggest effective AI career tools must balance diagnosis with prescription, ensuring students know both what to improve and how to improve it [24].

5.3 Practical Implications

The study has numerous practical implications. First, engineering programs should embed AI career feedback at strategic moments. Requiring Career Roadmap analysis during sophomore year, before declaring specializations, could promote intentional academic planning aligned with professional goals. Senior capstone courses could incorporate resume and job match assessments as formative exercises. Second, given advisor ratios exceeding 296:1, AI tools enable tiered advising. Students receive immediate baseline feedback through AI [25], identifying priority development needs. Human advisors then focus on specialized support around career pivots, significant gaps, or employment barriers like visa constraints. This preserves human expertise for contexts requiring relational trust while ensuring all students receive substantive guidance. Third, the Career Roadmap milestone structure enables longitudinal engagement. Students could interact semesterly, uploading updated resumes and comparing progress against prior analyses. This reinforces self-monitoring and provides tangible evidence of growth, enhancing self-efficacy. Fourth, AI tools democratize access to personalized feedback [25], [26] historically requiring social capital such as industry connections, alumni networks, or expensive coaching. For first-generation, international, or underrepresented students lacking familial guidance, these tools provide critical baseline support that can level the playing field. By offering immediate, industry-aligned feedback at scale, AI systems ensure that every student, regardless of background or resources, receives substantive career guidance. However, it is important to note that democratizing access is necessary but not sufficient for achieving equity in career outcomes. Underrepresented students face additional systemic barriers that feedback alone cannot address, such as implicit bias in hiring, visa restrictions, discriminatory workplace cultures, and limited professional networks . Effective implementation demands deliberate equity-focused design to ensure feedback acknowledges diverse career contexts (e.g., visa sponsorship requirements for international students), incorporates culturally responsive guidance that recognizes barriers underrepresented students face, and complements rather than replaces human advising relationships where marginalized students often find crucial advocacy and mentorship [27]. Institutions must integrate tools into required coursework to ensure universal access rather than positioning them as optional resources that advantaged students disproportionately utilize. Fifth, the tool should be regularly refined [26]. Students expressed interest in conversational interfaces enabling dialogue rather than static reports. Future iterations should incorporate chat functionality, allowing students to explore trade-offs between pathways or request elaboration on recommendations. Sixth, the tool provides students an opportunity to interact with a low-risk AI systems, develop AI literacy and be better prepared for the AI-augmented workforce [28], [29]. Finally, it is important to consider ethical considerations of the tool. Since the technology is still nascent, it is crucial to critically assess feedback provided by the tool [30], [31].

6. Conclusion, Limitations and Future Work

This study demonstrates that AI-driven career feedback systems can effectively enhance engineering students' self-regulated learning competencies related to professional development. By providing personalized, actionable guidance such tools address critical gaps in traditional career advising infrastructure and promote metacognitive awareness, strategic planning, and ownership of professional growth. The study is primarily limited by its small sample size (N=24) from a single institution that limits generalizability. Future research should examine effectiveness across diverse institutional contexts and larger student bodies. Additionally, the study measured intended rather than actual behavioral changes. Longitudinal follow-up assessing whether students completed recommended actions would provide stronger evidence of sustained impact. Finally, AI-generated feedback was not validated against expert career advisor judgments, which future work should address to ensure quality and identify potential biases. Additional future research could include (1) investigating how students with varying baseline readiness respond differently, (2) efficacy of conversational AI or chat features in enhancing engagement and overall tool effectiveness, (3) integrating the tool into courses and tracking longitudinal outcomes, (4) extending the system to support networking strategy, interview preparation, or salary negotiation to create comprehensive AI-mediated career support, (5) examining how AI tools can proactively address equity gaps through culturally responsive feedback for underrepresented students navigating industry barriers.

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Appendix A: ResuMatch Pro User Interface

Image A1: Landing Page for Workflow 1 (Resume Analysis)

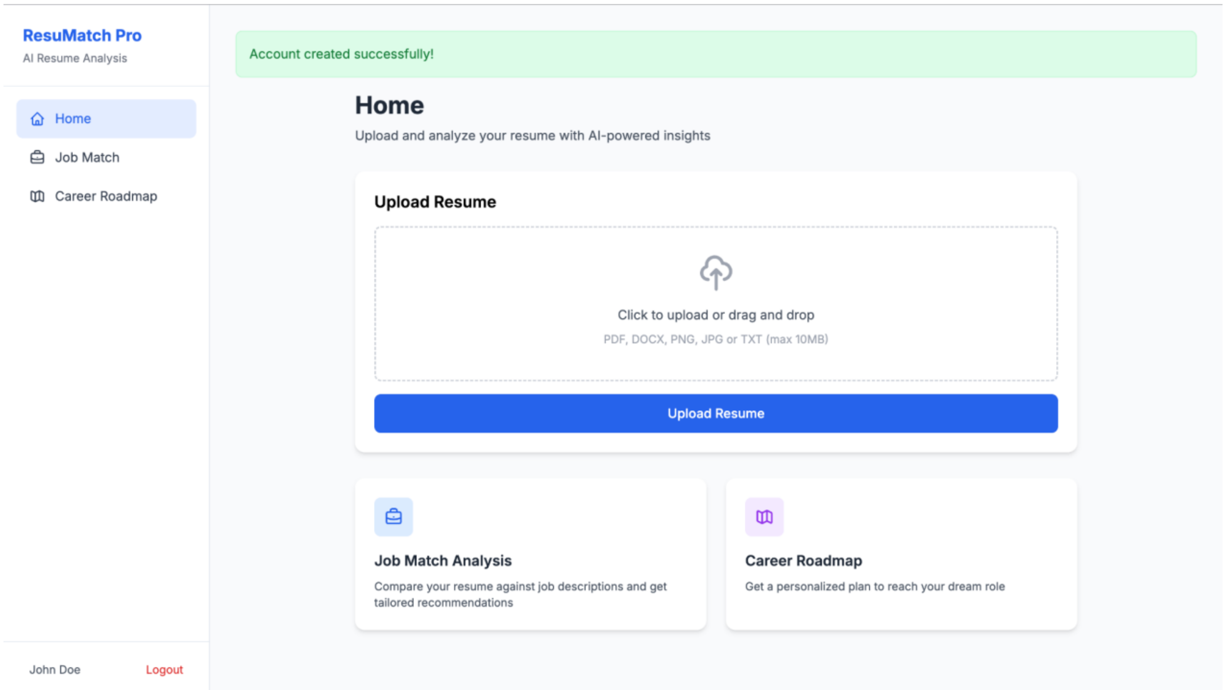


Image A2: Sample Results from Workflow 1 *(Partially Shown)*

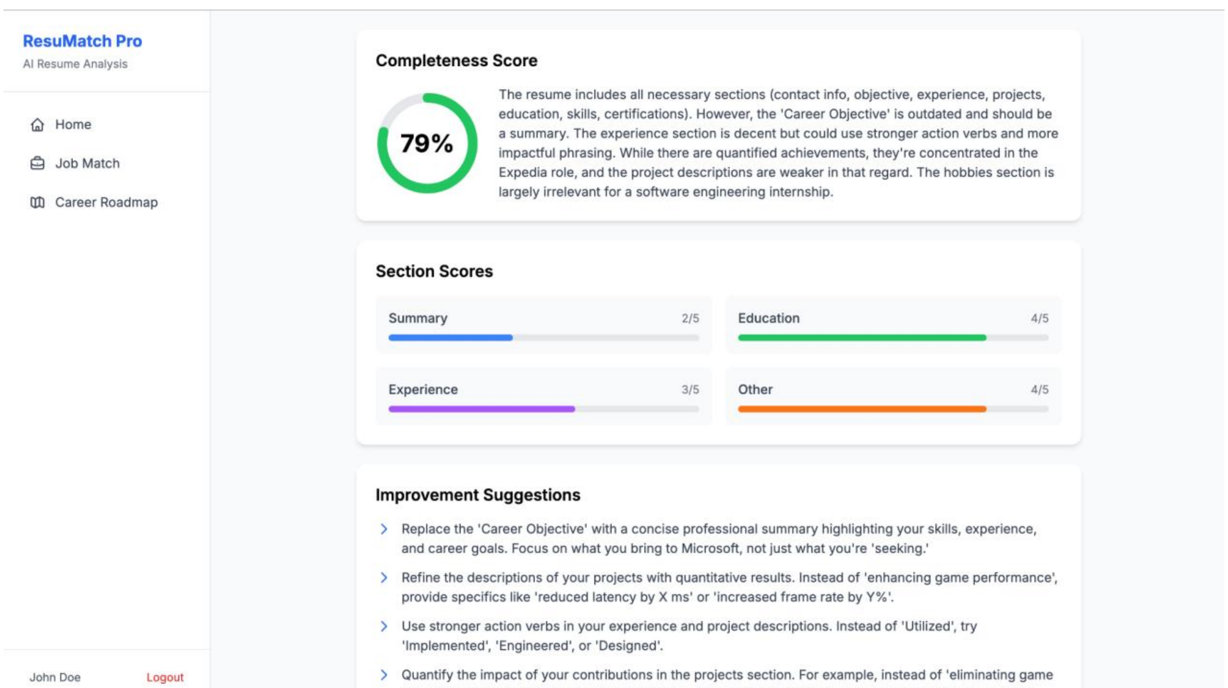


Image A3: Landing Page for Workflow 2 (Job Match Analysis)

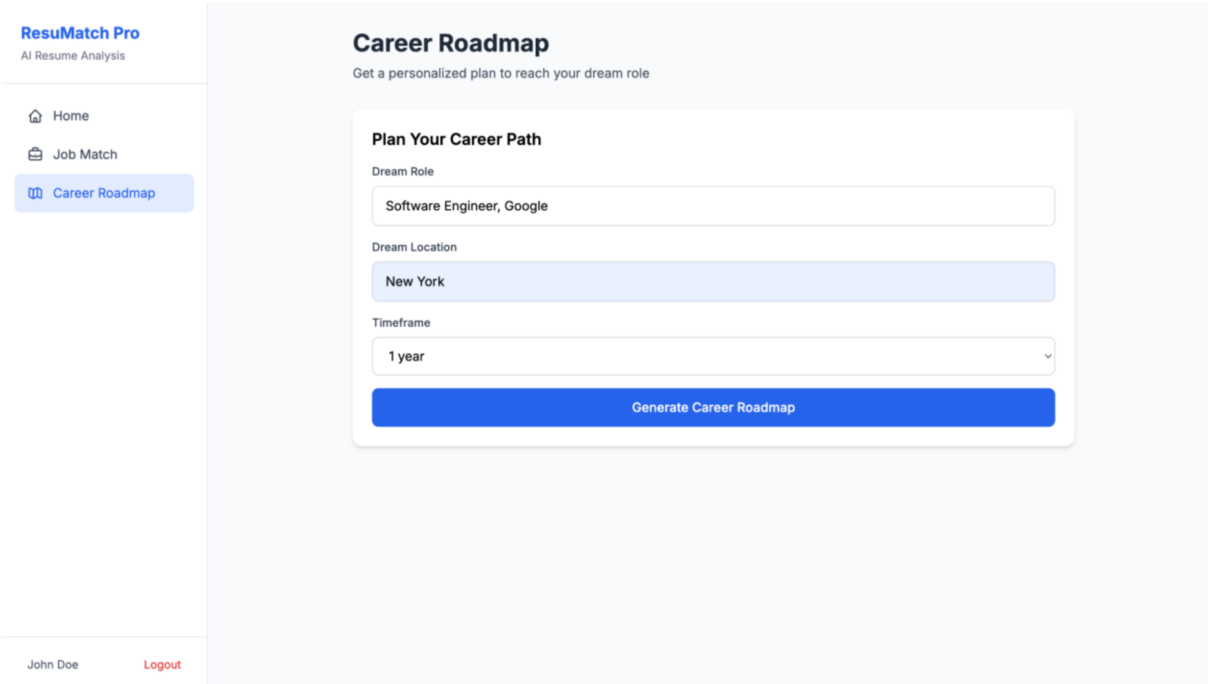


Image A4: Sample Results from Workflow 2 *(Partially Shown)*

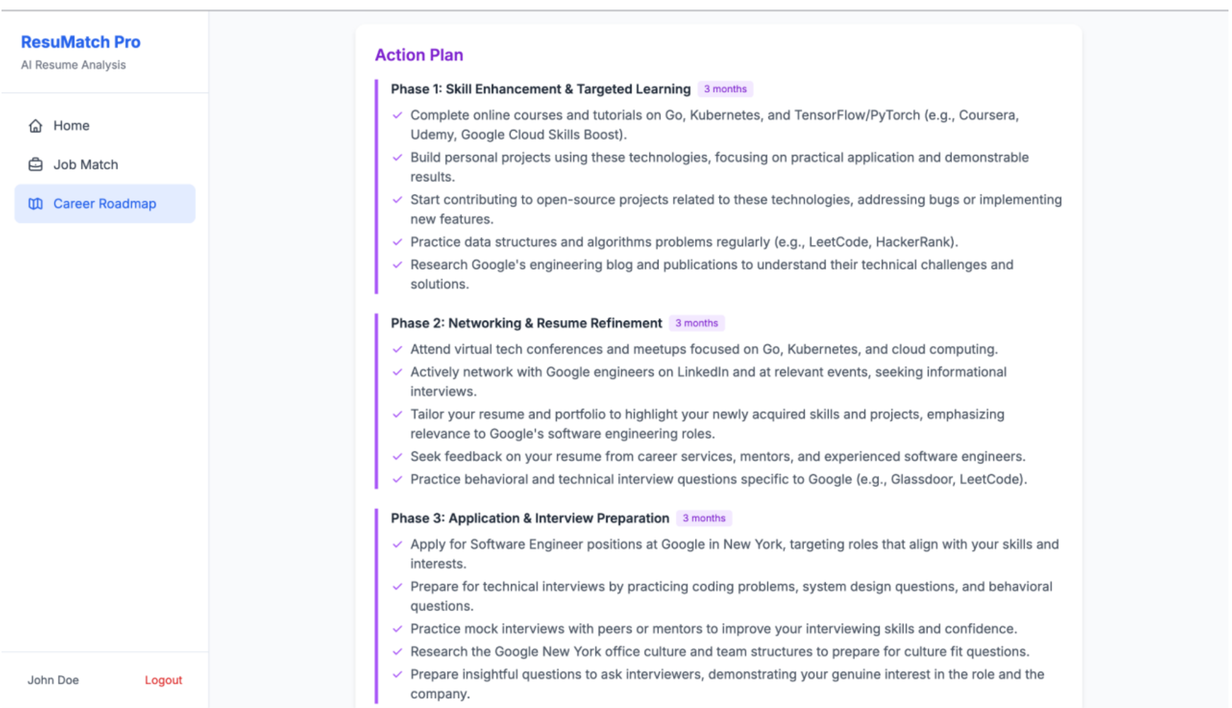


Image A5: Landing Page for Workflow 3 (Career Roadmap Analysis)

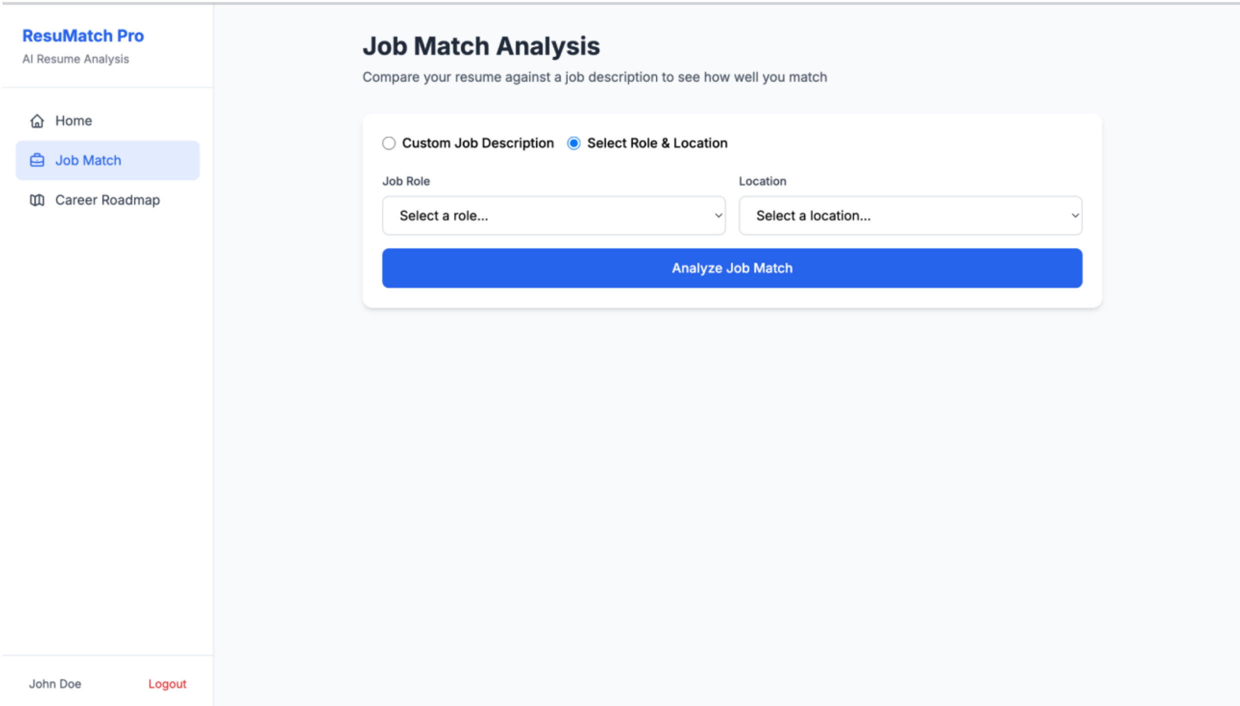
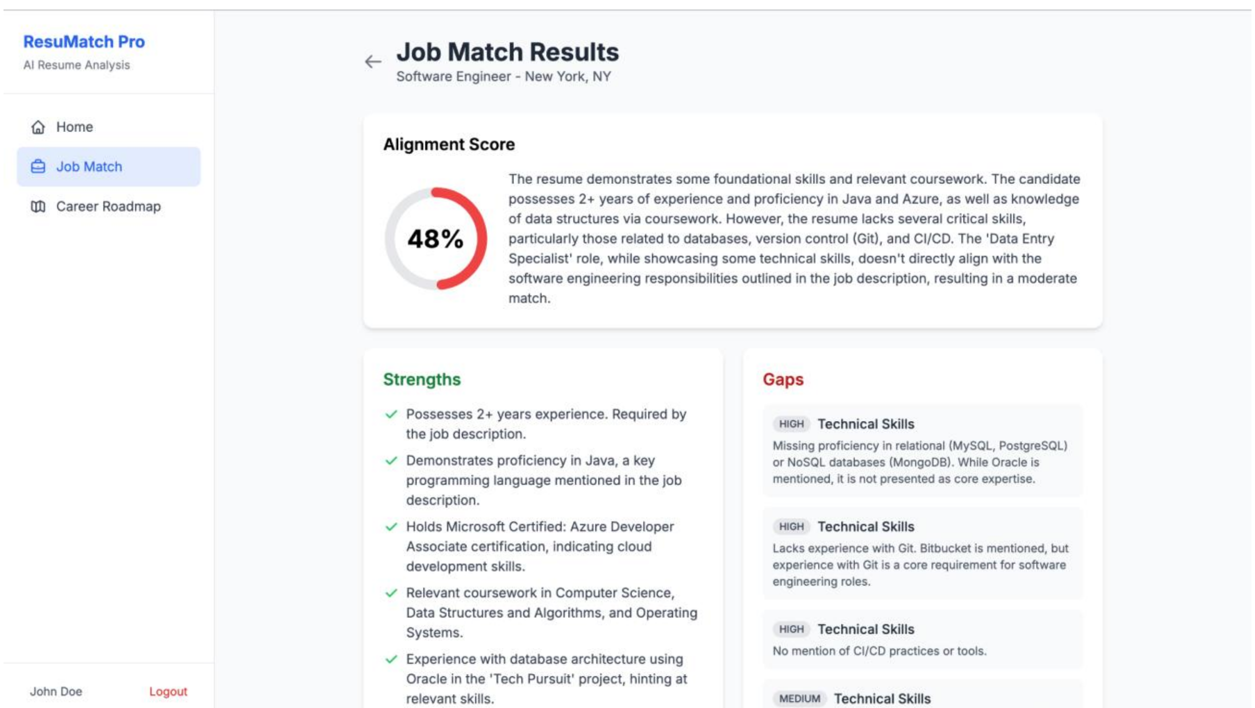


Image A6: Sample Results from Workflow 3 *(Partially Shown)*



Appendix B: Pre-Activity Survey Instrument

QN	Question Text
Q1. Demographics	
Q1_1	What is your current academic standing? (Sophomore / Junior / Senior / Graduate Student)
Q1_2	What is your major? [Text Entry]
Q1_3	How much work experience do you have? Include internships, co-ops etc. (0 / 1 / 2 / 3+ years)
Q2. Please rate your current level of agreement with the following statements:	
Q2_1	I can name the specific job title and company I want to work for in 3 years.
Q2_2	I can explicitly list the technical and professional skills I am currently missing for my target role.
Q2_3	I have a written or clearly defined plan (courses, projects, certifications) to bridge the gap between my current resume and my target career.
Q2_4	I am confident in my ability to identify industry-relevant projects without advisor assistance.

Note. Question 2 used 5-point Likert scales: 1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, 5 = Strongly Agree for all sub-items.

Appendix C: Post-Activity Survey Instrument

QN	Question Text
Q1. User Experience & Tool Perception	
Q1_1	Relevance: The ‘Individual Development Plan’ generated by the tool was relevant to my specific career goals.
Q1_2	Accuracy: The system accurately identified my competency gaps (e.g., missing specific technical skills or leadership experiences).
Q1_3	Scaffolding: The tool suggested projects or certifications I had not previously considered.
Q1_4	Actionability: The feedback provided is specific enough for me to act on immediately.
Q2. Self-Regulation & Growth	
Q2_1	I am now more aware of the specific competency dimensions (e.g., applied experience vs. technical expertise) employers look for.
Q2_2	I intend to change my future course selection or project choices based on this feedback.
Q2_3	I feel more equipped to manage my own professional development.
Q2_4	I have a clearer picture of my career trajectory now than I did before using the tool.
Q3	What was the most surprising skill gap or weakness the tool identified in your profile? [Text Entry]
Q4	Please list one specific project, course, or certification recommended by the tool that you plan to pursue. [Text Entry]
Q5	How did this AI-driven feedback differ from career advice you have received from human advisors or general online research? [Text Entry]

Note. Q1 and Q2 used 5-point Likert scales: 1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, 5 = Strongly Agree for each sub-items..

Appendix D: Descriptive Statistics

Table D1: Pre-Survey Results - Baseline Self-Regulated Learning Competencies (N=24)

QN	M	SD	Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
Q2_1	3.08	1.14	4 (16.7%)	5 (20.8%)	7 (29.2%)	6 (25.0%)	2 (8.3%)
Q2_2	2.83	1.05	2 (8.3%)	5 (20.8%)	8 (33.3%)	7 (29.2%)	2 (8.3%)
Q2_3	2.42	0.97	1 (4.2%)	3 (12.5%)	7 (29.2%)	10 (41.7%)	3 (12.5%)
Q2_4	3.25	1.07	5 (20.8%)	5 (20.8%)	7 (29.2%)	5 (20.8%)	2 (8.3%)

Note. Ratings based on 5-point Likert scale: 1 = Strongly Disagree, 5 = Strongly Agree. Values represent frequency (percentage).

Table D2: Post-Survey Results - Tool Perception Quality Dimensions (N=24)

QN	M	SD	Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
Q1_1	4.38	0.65	12 (50.0%)	9 (37.5%)	2 (8.3%)	1 (4.2%)	0 (0.0%)
Q1_2	4.29	0.69	10 (41.7%)	10 (41.7%)	3 (12.5%)	1 (4.2%)	0 (0.0%)
Q1_3	4.25	0.74	9 (37.5%)	10 (41.7%)	4 (16.7%)	1 (4.2%)	0 (0.0%)
Q1_4	4.46	0.59	13 (54.2%)	9 (37.5%)	2 (8.3%)	0 (0.0%)	0 (0.0%)

Note. Ratings based on 5-point Likert scale: 1 = Strongly Disagree, 5 = Strongly Agree. Values represent frequency (percentage).

Table D3: Post-Survey Results - Self-Regulated Learning Behavior Changes (N=24)

QN	M	SD	Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
Q2_1	4.42	0.58	12 (50.0%)	10 (41.7%)	2 (8.3%)	0 (0.0%)	0 (0.0%)
Q2_2	4.33	0.64	10 (41.7%)	11 (45.8%)	2 (8.3%)	1 (4.2%)	0 (0.0%)
Q2_3	4.38	0.58	11 (45.8%)	11 (45.8%)	2 (8.3%)	0 (0.0%)	0 (0.0%)
Q2_4	4.50	0.51	13 (54.2%)	10 (41.7%)	1 (4.2%)	0 (0.0%)	0 (0.0%)

Note. Ratings based on 5-point Likert scale: 1 = Strongly Disagree, 5 = Strongly Agree. Values represent frequency (percentage).

Table D4: Qualitative Response Themes: Surprising Skill Gaps Identified (N=24)
(Q3 from Post Survey)

Gap Category	n	%	Representative Examples
Experience Articulation Issues	16	66.7%	Quantifying achievements with metrics, demonstrating impact vs. listing tasks, using specific numbers
Soft Skills & Professional Competencies	5	20.8%	Leadership, communication, project management, budget management, networking, company event attendance
Specific Technical Skills/Certifications	3	12.5%	Security engineering keywords, specific programming languages, data analysis articulation, action verbs

Table D5: Qualitative Response Themes: Planned Developmental Actions (N=24)
(Q4 from Post Survey)

Action Category	n	%	Representative Examples
Technical Certifications	9	37.5%	AWS Certified Solutions Architect, Google Cloud certifications, data science credentials, ML model deployment
Specific Coursework/Skills	7	29.2%	Machine learning courses, system design, advanced programming languages, specialized technical training
Project-Based Learning	5	20.8%	Open-source contributions, portfolio applications, technical demonstrations, applied projects
Professional Development	3	12.5%	Networking events, mentorship seeking, achievement quantification, resume summary sections

Table D6: Qualitative Response Themes: AI vs. Human Advising Comparisons (N=24)
(Q5 from Post Survey)

Theme	n	%	Key Characteristics
Specificity & Personalization	13	54.2%	Detailed recommendations, actionable guidance, tailored to individual profile, faster than human advising
Accessibility & Immediacy	10	41.7%	Available on demand, no appointment scheduling needed, instant feedback, addresses uncertainty about resources
Limitations in Nuance	8	33.4%	Less contextual judgment, formatting oversights (e.g., page length), useful as starting point, better for novice users

Note. Sum of n is greater than 24, because many students mentioned multiple comparison points.