Development of a Prototype AI-Driven Career Guidance System for the Australian Construction Industry

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Abstract –

The construction industry is undergoing rapid transformation driven by digitalization, automation, and changing workforce structures. Despite these shifts, career guidance practices within the sector remain largely manual, fragmented, and poorly aligned with dynamic labor market conditions, limiting their effectiveness for workforce planning and innovation adoption. This study addresses this gap through the design and development of an artificial intelligence (AI)-driven career guidance system tailored to the Australian construction industry. The proposed system architecture comprises four integrated layers: knowledge base, reasoning algorithm, user interface, and cloud-based deployment environment. The knowledge base consolidates theoretical insights from a systematic literature review and occupational data from government and industry sources. A hybrid reasoning approach combining rule-based logic and large language model (LLM) capabilities enables automated, scalable, and personalized career recommendations. The user interface was delivered through a web-based platform to support intuitive design and ease of use. Deployment was implemented through Amazon Web Services (AWS) Elastic Compute Cloud (EC2) to support scalable and reliable system hosting. After the prototype was developed, 32 construction students were invited to pilot the system and complete a questionnaire on perceived usefulness, usability, and impact, while also providing recommendations for improvements. This study contributes to construction technology management and service innovation by demonstrating how AI enabled automation tools can support workforce development, enhance career decision making, and inform strategic talent pipelines for education providers and industry stakeholders.

Keywords –

Artificial Intelligence (AI); Australia; career pathways; construction industry; Large Language Model (LLM)

1 Introduction

Technological advancement and the growing emphasis on digitalization and sustainability have substantially increased the complexity of construction work. Modern construction roles now demand not only technical and project management competencies but also digital literacy, data analysis, and sustainability-related skills [1]. For example, the rise of Building Information Modelling (BIM), digital twin technologies, and green building practices has transformed traditional site-based positions into multidisciplinary roles requiring hybrid technical and analytical capabilities [2]. As a result, the career landscape in construction is rapidly evolving, creating new opportunities while intensifying the ongoing skills shortages that threaten the industry's long-term sustainability and productivity.

Career counselling and guidance have long been recognized in literature as key measures for supporting informed and sustainable career decisions [3]. However, despite its importance, traditional career guidance remains limited in both scale and effectiveness. The advice provided rely heavily on the expertise and personal judgement of individual career advisers, and often lack up-to-date, industry-specific insights [4]. For example, career advisers who are unfamiliar with modern construction technologies or professional roles may unintentionally reinforce outdated stereotypes or overlook emerging career pathways such as digital engineering, sustainability consulting, or project data analysis. These limitations highlight the need for more systematic, scalable, and data-driven approaches to career guidance that can deliver accurate, personalized, and up-to-date information aligned with the realities of the modern construction industry.

The rapid advancement of artificial intelligence (AI) and Large Language Model (LLM) in recent years has introduced new opportunities to address many of the limitations of traditional career counselling. Previous studies have attempted to use AI as a career advisory tool, demonstrating the potential of AI systems to simulate the functions of a human career coach. For example, Kulugh, et al. [5] developed an AI-based career recommendation chatbot that analyzed students' educational profiles to suggest potential occupational paths, while Cheng and Liang [6] combined natural language processing (NLP) with machine learning classifiers to align user goals with their backgrounds. These developments have marked a shift from static career databases to dynamic, conversational systems capable of analyzing user profiles and generating adaptive career suggestions. However, most existing AI career coaching tools are designed for general audiences and rely on global or non-specialized datasets, lacking the domain-specific depth required to address the distinct structure and workforce characteristics of the Australian construction industry. As noted by Miller, et al. [7], integrating structured industry knowledge into AI systems significantly enhances their precision, contextual relevance, and trustworthiness.

To fill this gap, this study aims to design and develop an AI-powered career guidance system for the Australian construction industry, supporting students, graduates, and career changers in making informed career decisions.

2 System Architecture Design

2.1 Knowledge Base Layer

A knowledge base layer serves as the foundation of the system by providing structured and domain specific information to suit reasoning algorithm. It ensures that the AI operates with targeted knowledge rather than relying solely on general purpose information, thereby reducing the risk of irrelevant outputs and hallucinations [8]. In this study, the knowledge base layer incorporates a career information repository that was developed to provide data-driven and evidence-based insights tailored to the Australian construction industry.

To establish the foundation for developing a comprehensive career information repository, this study first identified key factors influencing career decisions in the construction industry through a systematic literature review. As a widely used research method, a systematic literature review facilitates the identification, evaluation, and synthesis of existing studies on a specific topic [9]. The thematic synthesis approach was applied, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach to ensure transparency, reproducibility, and methodological rigor.

Scopus was selected for its comprehensive coverage of peer-reviewed journals in construction management, engineering, and career development. An initial title search using "construction" and "career" returned 493 papers. A three-stage screening process was applied. First, filters limited results to English-language journal or journal/review articles published after 2015 from comparable labor markets (Australia, US, UK, New Zealand, Canada), reducing the set to 110 papers. Second, titles and abstracts were manually screened to confirm relevance to construction careers and full-text availability, yielding 40 papers. Finally, only studies examining or proposing factors influencing career choice or development in construction were retained, resulting in 14 papers. This number aligns with other systematic reviews in the construction field [10].

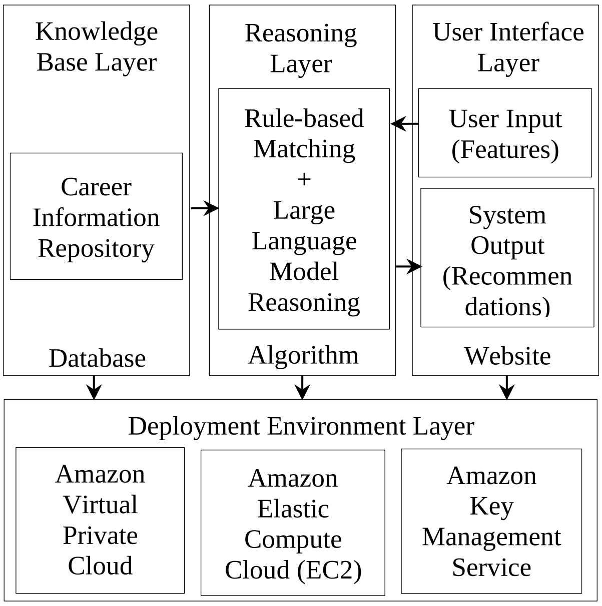

Figure 1. System architecture

The selected papers were analyzed using thematic analysis conducted in Lumivero NVivo 14, which facilitates efficient data management, coding, and theme development [11]. Each paper was reviewed manually, and descriptive codes were assigned to text segments that represented influential factors shaping careers in the construction industry. Codes with overlapping meanings were merged to reduce redundancy. Based on the thematic synthesis, the factors influencing career decisions were grouped into two major categories. Extrinsic factors refer to external conditions and contextual incentives that shape an individual's career choices, including opportunities for future growth, salary expectations, work environment, flexibility, and workplace diversity. Intrinsic factors relate to internal motivations and personal features that influence career preferences, educational background, technical competencies, soft skills, work style, and prior exposure to the industry. Table 1 summarizes the mapping of factors identified across the 14 reviewed studies.

Based on those key factors identified through the systematic literature review, the career information repository was designed to incorporate 16 features, encompassing general role information, extrinsic factors, and intrinsic factors, as summarized in Table 2.

Table 1. Factors mapping overview

	Factors	Literatures
Extrinsic	Future growth	1, 2, 4, 11, 13,14
	Salary	1, 2, 11
	Work environment	1
	Flexibility	2, 3, 7, 12, 13
	Diversity	1, 4, 7, 8, 9, 13
	Physical demand	1
Intrinsic	Education	5, 9
	Technical skills	1
	Soft skills	8, 9, 10, 13
	Work style	2, 6, 7
	Prior exposure	3, 5, 8, 9, 10

Note: 1 = [12]; 2 = [13]; 3 = [14]; 4 = [15]; 5 = [16]; 6 = [17]; 7 = [18]; 8 = [19]; 9 = [20]; 10 = [21]; 11 = [22]; 12 = [23]; 13 = [24]; 14 = [25].

Table 2. Features included in the knowledge base

	Features	Description
Role	*discipline*	Construction disciplines
	role_description	General scope of daily work
	typical_titles	Variations in job titles
Extrinsic	*future_growth*	Growth outlook for the role
	career_pathway	Example progression
	salary_range	Annual salary range
	work_envir	The primary work location
	outside_hours	Work outside standard hours
	location_flex	Flexibility in work location
	hour_flex	Flexibility in work hours
	gender_ratio	Percentage of women
	physical_dem	Level of physical effort
Intrinsic	*minimum_edu*	Entry qualification required
	technical_skills	Technical competencies
	soft_skills	Interpersonal skills
	work_style	Characteristics of the role

The knowledge base of the prototype was scoped to focus on entry-level roles in the Australian construction industry, reflecting the initial development stage and time and budget constraints, with additional roles to be incorporated in future system iterations. A search was conducted on three commonly used job seeking websites, SEEK, CareerOne, and Workforce Australia, using the keyword “entry level” and the industry classification “construction”. Additional roles were identified through open discussions with industry professionals and members of the research team with backgrounds in the Australian construction industry, informing the selection of roles to be included. As a result, the knowledge base captured 70 commonly found roles across 10 disciplines in the Australian construction industry, as outlined below.

1. Construction Management and Project Management
2. Quantity Surveying and Cost Management
3. Civil Engineering and Structural Engineering
4. Architecture, Design, and Urban Planning
5. Building and Construction Trades
6. Health, Safety, Environment, and Quality
7. Building Surveying and Certification
8. Property, Real Estate, and Facilities Management
9. Mechanical, Electrical, and Services Engineering
10. Surveying, Geospatial, and Geographic Information System (GIS)

A web scraping process was conducted to collect career-related data from a range of credible public sources (n= 83), including government websites, industry associations, educational institutions, and major job-seeking platforms. The scraping was implemented in Python using the BeautifulSoup and Requests libraries to extract structured information. To ensure accuracy and data integrity, the final knowledge base was manually reviewed and validated by the research team, with inconsistencies cross-checked against official government and industry sources.

2.2 Reasoning Layer

The reasoning layer refers to the component responsible for processing user input, matching with the knowledge layer, and generating role recommendations. The core of this layer is the algorithms, which is designed to combine rule-based matching with LLM reasoning, as suggested by recent studies in information systems and artificial intelligence [26]. This hybrid approach allowed the system to balance accuracy with flexibility in handling complex and variable inputs. Among the 16 features, nine were utilized within the reasoning layer, while the remaining features were presented as system outputs.

Categorical features, including *work_envir*, *physical_dem*, *outside_hours*, *location_flex*, *hour_flex*, and *work_style* were designed to be matched using rule-based methods to ensure accuracy and consistency, as these data points in the knowledge base were predefined and discrete. Each feature was assigned a discrete score based on the degree of correspondence between user preferences and role characteristics.

Textual features, namely *minimum_education*, *technical_skills*, and *soft_skills*, were scored using LLM reasoning, as these inputs contain diverse linguistic expressions, synonyms, and contextual nuances that cannot be effectively captured through rule-based matching alone. To guide the LLM’s reasoning process and ensure consistent evaluation across users, prompt engineering techniques were applied to reduce hallucinations. It refers to the process of designing structured instructions that guide the LLM to generate accurate, consistent, and contextually appropriate responses. The template is presented below.

- System Role: You are a professional career advisor with expertise in the Australian construction industry.
- Task: Analyze the user's background and match it with suitable roles using the knowledge base.
- Scoring Rules: Assign numerical scores for each feature based on the level of alignment between the user's profile and role requirements. Use continuous scoring rather than fixed anchor points to allow finer differentiation. Clearly identify matched and unmatched features, highlighting areas of strength and potential improvement.
- Response Structure: Strengths: Your background aligns well with this role because [analysis]. Areas for Development: Areas that may need further development include [analysis]. Interpersonal Skills: Employers often look for [skills]. Other Recommendations: To expand your career options, [personalized advice, industry associations, mentorship].
- Output Requirements: Return all responses in valid JSON format. Do not include any text outside the JSON structure. Maintain a warm, professional, and easy to understand tone using Australian English. Do not recommend qualifications lower than the user's current education level.

The total score for a given role r, expressed on a 100-point scale, is calculated as:

$$S_{rule}(r) = 5 \times \sum_{i=1}^{6} m_i \quad (1)$$

$$S_{LLM}(r) = (0.4 \times S_{edu} + 0.15 \times S_{tech} + 0.15 \times S_{soft}) \quad (2)$$

$$S_{final}(r) = S_{rule}(r) + S_{LLM}(r) \quad (3)$$

where m_i denotes the discrete score based on the degree of correspondence (0 for mismatch, 0.5 for partial match, and 1 for exact match). The terms S_{edu}, S_{tech}, and S_{soft} represent the feature scores (each on a 100-point scale) assigned by LLM. The weightings used in the formula were determined through research team discussions and remain adjustable through future performance testing. Future versions will also allow users to adjust the weighting scheme according to their preferences. In addition, a comparison was conducted to assess the performance of the system across five LLM backends: GPT-4.1, Claude-sonnet-4, Gemini-2.5-flash, Qwen-plus, and Deepseek-chat. Using ten participant resumes, each model generated career recommendations. The outputs were evaluated by three industry experts within the research team, each with over five years of experience in the Australian construction sector. Scores were assigned on a 1–5 scale, where 1 indicates the lowest level of satisfaction and 5 indicates strong satisfaction. Processing time and estimated computational cost were also recorded. Table 3 summarizes the results.

Table 3. LLMs Comparison Results

Model	Score ($\mu \pm \sigma$)	Time (s) ($\mu \pm \sigma$)	Cost (USD)
GPT-4.1	**4.45 ± 0.37**	10.92 ± 0.94	1.08
claude-sonnet-4	3.84 ± 0.34	11.60 ± 0.25	1.1
gemini-2.5-flash	3.78 ± 0.34	30.63 ± 2.50	0.96
qwen-plus	3.78 ± 0.34	**8.26 ± 0.34**	0.12
deepseek-chat	4.00 ± 0.34	15.65 ± 0.69	**0.05**

Note: μ = the mean value; σ = the standard deviation.

The results revealed performance of trade-offs among the models. GPT-4.1 achieved the highest expert-rated quality, indicating its suitability for high-stakes or decision-critical applications. Deepseek-chat demonstrated the most favorable cost efficiency while maintaining competitive performance, supporting scalable deployment scenarios. Qwen-plus consistently delivered the fastest response times, making it well-suited for interactive applications with modest quality trade-offs. Claude-sonnet-4 showed moderate performance across all metrics without a clear advantage, whereas Gemini-2.5-flash exhibited relatively higher latency without commensurate gains in quality or cost. Future work plans to allow users to select and compare different models within the system.

2.3 User Interface Layer

The user interface layer refers to the component through which users interact with the system. It connects with the reasoning layer to present outputs in clear and readable text. It collects user input, transmits the data to the reasoning layer for analysis, and presents the resulting recommendations in an accessible and user-friendly format. A web-based platform was chosen as the delivery format, as it offers broad accessibility, ease of deployment, and the ability to integrate seamlessly with backend services. The user interface and user experience design followed principles of clarity, simplicity, and accessibility, ensuring that the system is easy to read, navigate, and interact with. This layer was developed using python, Hypertext Markup Language (HTML), and JavaScript connecting to the reasoning layer.

To improve user convenience and minimize manual data entry, a resume importing function was embedded in the interface using spaCy and PyPDF2 for named-entity extraction. This feature allows users to upload their resume in Word or PDF format after consenting to the Privacy Protection Statement. Uploaded resumes are converted into plain text, segmented into key sections (education, skills, certifications), and analyzed using pattern matching and entity recognition to identify relevant features. The extracted data are automatically mapped to the corresponding input fields in the interface, allowing users to review and edit the pre-filled information before submission. All files are processed temporarily and deleted after use to ensure privacy protection.

Users are required to complete three sections. The first section focuses on educational background, where users list their academic qualifications, certifications, and professional licenses. An example entry is provided to guide users in completing this section. The second section, skills and experience, collects information on users' technical skills, software proficiency, and interpersonal or soft skills. To assist users in formulating their responses, example suggestions are displayed beneath each input field, referencing common competencies in the construction industry. The final section, interest assessment, consists of six multiple choice questions corresponding to the features in the knowledge base, including work environment, physical demands, outside hours, location flexibility, hour flexibility, and work style. Each question is phrased in plain English to ensure comprehension and ease of response. Figure 2 presents the developed prototype.

Upon completion of the three sections, the results page generates a list of five career roles that best align with the user profile based on the provided inputs. Each role includes a brief overview, key characteristics, and AI-generated insights including strengths, areas for improvement, and recommendations for career development. Figure 3 presents an example of a recommended role output screen.

2.4 Deployment Environment Layer

The deployment environment provides the infrastructure necessary for hosting and operating the AI-powered career guidance tool online. It ensures system availability, data security, and scalability for handling multiple user requests simultaneously. Common deployment approaches include cloud-based, on-premises, and hybrid environments. In this study, cloud-based deployment was selected using Amazon Web Services (AWS) due to its scalability, reliability, and cost efficiency [27]. The system was deployed on Amazon Elastic Compute Cloud (EC2), which hosts the application backend, executes rule-based and LLM-driven computations, and manages communication with the knowledge base and user interface. EC2 offers elastic computing resources that can automatically scale to accommodate variable user demand, ensuring consistent system performance. The deployment operates within an Amazon Virtual Private Cloud (VPC), which isolates the system components and controls inbound and outbound network traffic, providing an additional layer of network security. The AWS Key Management Service (KMS) was used to encrypt data stored and processed on the EC2 instance, protecting sensitive information such as user inputs and uploaded resumes. This encryption framework ensures that data confidentiality is maintained in accordance with privacy and security standards. Data exchange between the user interface, backend, and external APIs is managed through AWS Data Transfer, which ensures stable and secure data transmission with low latency.

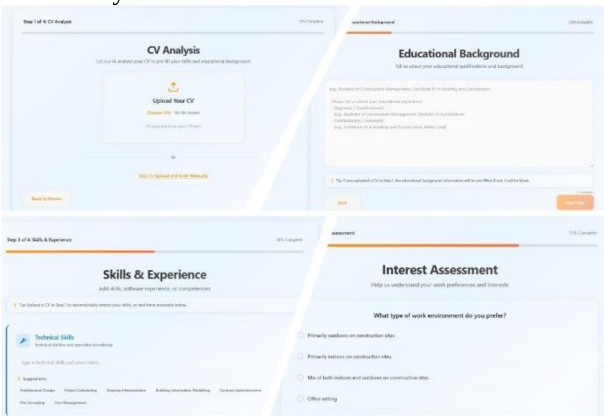

Figure 2. Developed web pages

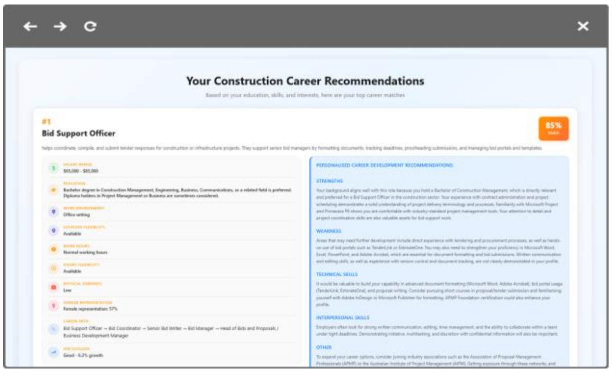

Figure 3. Results page

The process begins with launching an EC2 instance, followed by configuring the security group to define access permissions. The website code is then deployed to the instance, after which the domain name is configured to enable public access. System monitoring is subsequently set up to track performance and availability. A decision point is used to verify whether the website is running as expected. If issues are identified, troubleshooting is performed before rechecking system status. Once the website is confirmed to be running successfully, the deployment process concludes.

3 Pilot User Experience

After the prototype was developed, users were invited to experience the system and provide feedback to inform future improvements. A total of 42 students participated in the workshops. The questionnaire responses were screened for completeness and validity prior to analysis. Incomplete submissions (n=2), responses with missing demographic information (n=5), or careless responses (n=3; those in which participants selected the same answer for all questions) were excluded. The final dataset consisted of 32 valid responses. Descriptive analysis was performed using Microsoft Excel to summarize quantitative data, while qualitative feedback was analyzed through manual coding to identify recurring themes and improvement suggestions. The majority were aged between 18-25 years, with 59.3% identifying as female. Most participants (62.5% of total) reported having no prior work experience in the Australian construction industry, reflecting the target user group of the tool.

The quantitative section of the survey consisted of 10 Likert-scale items rated from 1 (“strongly disagree”) to 5 (“strongly agree”), measuring three key constructs: usefulness, ease of use, and impact.

Usefulness refers to the extent to which users believed that the tool provided relevant and insightful career guidance. Three items were adapted from Venkatesh and Davis [28] with a Cronbach’s alpha of 0.72. *Ease of use* refers to the extent to which users find the system intuitive and user-friendly. Four items were adapted from Venkatesh and Davis [28] with a Cronbach’s alpha of 0.88. *Impact* refers to the extent to which users found the tool had an impact on their career and introducing new potential roles within the construction industry. Four items were adapted from Gedrimiene, et al. [29] with a Cronbach’s alpha of 0.76. Table 3 presents quantitative results, indicating generally favorable perceptions across all statements.

Two open ended questions were used to capture qualitative insights from participants, focusing on which functions could be improved or made easier to use, and which additional functions users would like to see incorporated into the tool. The findings informed the future development roadmap, which is discussed in the following section.

4 Future Development Roadmap

Regarding existing functions, the most frequently mentioned area for improvement was system response time, noted by more than 40% of users. The commonly requested improvement, supported by over 35% of participants, was the ability to download and share results directly. At present, users can only export their results as a PDF using the browser’s print function and share them manually. During the user evaluation workshops, several participants were observed taking photos of their results to keep personal records. Integrating a built-in saving and sharing feature, such as generating downloadable PDF summaries or enabling direct sharing through emails, would further improve the system’s usability and accessibility.

Table 4. Descriptive Analysis Results

	Statements	Mean
Usefulness	1. The tool’s recommendations were relevant to my skills and experience.	4.09
	2. The tool provided career options that matched my interests.	4.03
	3. The tool offered new career options I had not previously considered.	3.94
Ease of Use	4. The tool was easy to use.	4.44
	5. I felt confident in using the tool.	4.22
	6. The design and layout were clear and intuitive.	4.25
	7. The tool delivered what I expected it to.	3.94
Impact	8. The tool increased my confidence in making career decisions.	3.84
	9. The tool encouraged me to research new career pathways.	4.03
	10. I want to recommend this tool to others.	4.00

When participants suggested additional functions for future development, the most frequently recommended enhancement was career pathway visualization. Currently, the prototype presents future pathways in text only, without visual or interactive elements. Participants suggested that an interactive flow diagram or progression map could help users better understand advancement routes in construction, including transitions from entry-level to middle and senior roles. Such visualization could also enhance user engagement and learning effectiveness, as graphical tools have been shown to enhance users’ comprehension of complex information and improve engagement [30].

Another widely supported suggestion was the introduction of an AI-powered mock interview practice module, recommended by approximately half of the participants. This aligns with Shi and Wang [31] emphasizing the value of simulated interview experiences in building communication confidence and employability skills. Such function could offer users a low-pressure environment to practice common industry questions, receive feedback, and prepare for recruitment. Additionally, over 35% of participants proposed the inclusion of an AI-powered chatbot to make the system “more interactive”. This chatbot could serve dual purposes, including facilitating mock interview interactions and providing real-time responses to user queries about job recommendations, role descriptions, and next steps. Embedding conversational AI in this way would enhance engagement and deliver a more dynamic, personalized user experience.

In addition, over 40% of users suggested adding a peer stories or role model showcase section. This suggestion aligns with Perrenoud, et al. [32], highlighting the lack of visible role models as a barrier to participation, particularly among women and underrepresented groups in construction. Integrating authentic career stories could humanize the data-driven recommendations, demonstrate diverse pathways to success, and inspire users through relatable real-world examples. Developing this feature would, however, require collaboration with industry partners and professional associations to source and verify participant narratives.

Last but not the least, several participants recommended linking the system directly to current job postings to improve the immediacy and practicality of its recommendations. This could potentially be achieved by connecting the platform with established job-seeking websites such as SEEK or CareerOne. However, implementing such integrations may present challenges related to privacy, data sharing, and potential conflicts of interest. Future research could explore partnership models or API-based data-sharing frameworks that ensure compliance while providing users with up-to-date labor market insights.

5 Conclusion

This study presented the design and development of an AI-powered career guidance system tailored to the Australian construction industry as a technology enabled service innovation. The positive pilot user experience highlights the potential of automation tools and AI to support technology management, workforce planning, and innovative career guidance practices within the construction sector.

This study has several limitations that also present opportunities for future development. First, as the initial stage, the current prototype focuses solely on entry-level positions in the construction industry. Expanding the system to include mid- and senior-level roles would allow users to explore long-term career trajectories and progression pathways within the sector. Second, the features used in the prototype were not exhaustive. Future stages could incorporate additional matching features, such as language proficiency, cultural background, and personal values, to provide a more holistic representation of career decision factors. As with most LLM-based systems, the model remains sensitive to prompt formulation and exhibits potential brittleness, which may affect consistency in outputs. Future work could refine prompt-engineering strategies or adopt hybrid architectures that combine deterministic logic with adaptive AI reasoning to improve reliability. Additionally, future work should include comparison with human advisors to benchmark the system's performance, enabling a systematic evaluation of the relative advantages and limitations of AI- and human-based career guidance. Technical constraints also exist in relation to AWS deployment, including dependence on stable internet connectivity, ongoing server maintenance costs, and token usage fees associated with LLM processing. To enhance scalability and sustainability, future implementations could explore serverless architectures to enable wider accessibility and continuous operation. Last but not least, As the system provides career recommendations, potential bias and fairness issues must be carefully considered. Measures such as bias auditing can help identify whether recommendations systematically differ across demographic groups, such as gender. Providing transparent explanations for recommendations may also help users understand how suggestions are generated. Future work should incorporate bias monitoring and responsible AI practices to support inclusive and equitable career guidance.

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