

AI-Powered Women's Entrepreneurship Ecosystems: A Review of Personalized Learning

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Abstract— Career guidance has traditionally relied on fixed assessments and generalized advice. Artificial Intelligence (AI) is gradually changing this, making guidance more personalized and more dependent on data. Recent studies have looked at career recommendation, conversational assistance, mentoring, adaptive learning, skill-gap analysis, explainable recommendation, and multilingual support. These lines of work differ widely in their goals, methods, target users, datasets, and evaluation practices. This paper reviews eight selected studies that together cover these developments. It considers how large language models, machine learning, semantic similarity, interest-based profiling, adaptive assessment, knowledge graphs, and explainable AI are applied in career-development settings. The literature shows personalization drawing increasingly on skills, interests, education, career intent, performance, and interaction history. Skill-gap analysis links recommendations to learning pathways, conversational AI makes guidance more natural, and explainability is becoming a requirement for user trust. Several challenges remain: career recommendation and skill development are still treated separately, personalization is rarely continuous, evaluation methods are inconsistent, and few systems bring multiple guidance functions together. The paper closes by outlining research directions in adaptive personalization, explainable recommendation, integrated learning pathways, multilingual interaction, feedback-driven design, and real-time career information.

Keywords— Artificial Intelligence, Career Guidance, Personalized Learning, Recommendation Systems, Skill Development, Skill-Gap Analysis, Explainable AI, Large Language Models, AI Mentoring.

I. INTRODUCTION

Planning a career is harder than it used to be. Job roles appear and disappear quickly, skill requirements keep shifting, and learners face an overwhelming amount of information. Traditional guidance usually depends on standardized tests, fixed career paths, or general counselling. These methods are useful, but they often pay little attention to a person's individual interests, existing skills, goals, and learning needs.

AI offers ways to address this. Machine learning, recommendation systems, natural language processing, semantic analysis, and large language models can work with many kinds of user information to produce individualized suggestions. As a result, recent research has moved past simple career prediction and now covers skill-gap identification, adaptive learning, conversational assistance, mentoring, interview preparation, and explainable recommendation [1]–[8].

Conversational AI is one clear strand of this work. Wang et al. proposed AdaptJobRec, a career recommendation system driven by a large language model, which classifies query complexity, processes memory, decomposes tasks,

and calls personalized recommendation tools [1]. Their results suggest that an agentic design can handle both simple and complex career queries without wasting computation.

Mentoring is another strand. Luo et al. tested several large language models for personalized mentoring in computing, using different student profiles [2]. They looked at how well each model tailored its responses and stressed that human evaluation and human mentors remain necessary.

Other studies take a broader view. AI NEWUS combines adaptive learning, dynamic assessment, placement preparation, AI-based mock interviews, feedback, and performance analytics in one platform [3]. Shirtode et al. surveyed AI-based career recommendation, covering machine learning, recommendation systems, skill-gap analysis, fuzzy logic, and deep learning, and found that existing systems are fragmented [4].

Interest models have also been used for personalization. Roy and Sharma applied the RIASEC model alongside Decision Tree, XGBoost, and Support Vector Machine classifiers [5]. Sankalp goes further by combining semantic matching, sentiment analysis, knowledge graphs, labour-market data, multilingual interaction, and adaptive recommendation [6].

Patil et al. surveyed personalized career guidance and preparation systems and called for more integrated approaches that cover career discovery, skill development, and preparation together [7]. Finally, AspireNextGen focuses on explainability, pairing structured role-skill mapping with semantic similarity and controlled natural-language generation [8].

Taken together, these studies show real progress, but the field remains scattered. Each system tackles a different part of the career-development process. This paper therefore reviews the eight studies to draw out their shared approaches, limitations, and possible future directions.

II. REVIEW METHODOLOGY

This paper follows an integrative narrative-review approach to examine recent work on AI-based personalized career guidance and skill development.

Eight papers were chosen because, between them, they cover the main research directions in the area: conversational career recommendation, AI-based mentoring, adaptive learning and career preparation, surveys of AI recommendation techniques, machine-learning-based personalized guidance, hybrid and multilingual guidance, surveys of guidance and preparation systems, and explainable career and skill recommendation.

Each paper was read with the same questions in mind: what problem it addressed, who the target users were, how personalization and user profiling were handled, whether it offered career recommendation, skill-gap analysis, or learning support, which AI and machine-learning techniques it used, how explainable it was, how it was evaluated, and what its main findings, limitations, and suggested future work were.

The studies differ in datasets, populations, algorithms, metrics, and aims, so their numerical results were not pooled or statistically compared. The goal is instead to identify common patterns, methodological trends, limitations, and open opportunities in the field.

III. LEARNING III. OVERVIEW OF SELECTED RESEARCH

Table I. Overview of the Selected Research Papers

No.	Research Paper	Main Research Focus
[1]	AdaptJobRec: Enhancing Conversational Career Recommendation through an LLM-Powered Agentic System	Conversational career recommendation using agentic AI
[2]	Assessing Personalized AI Mentoring with Large Language Models in the Computing Field	Personalized AI mentoring
[3]	AI NEWUS: An AI-Powered Career Guidance and Placement Preparation Platform	Adaptive learning and career preparation
[4]	A Survey on Artificial Intelligence Based Career Recommendation Systems: Techniques, Architectures, and Research Gaps	Survey of AI career recommendation techniques
[5]	AI-Powered Career Guidance: A Scalable Model for Personalized Recommendations	RIASEC-based personalized career recommendation
[6]	Sankalp: AI-Powered Career Guidance System	Hybrid AI-based career guidance
[7]	A Survey on AI-Based Personalized Career Guidance and Preparation Systems	Personalized guidance and preparation
[8]	AspireNextGen: An Explainable AI-Powered Personalized Career and Skill Recommendation System	Explainable career and skill recommendation
[9]	A Multi-Agent Conversational Recommender System	Multi-agent conversational recommendation

IV. PERSONALIZATION IN AI-BASED CAREER GUIDANCE

A. User Profiling

Profiling the user is the starting point for any personalized guidance. The reviewed studies draw on skills, interests, academic background, career objectives, professional level, and free-text descriptions [1], [2], [5], [8].

AdaptJobRec shows why conversational context matters. Rather than treating each query in isolation, it can bring in earlier interactions when a request is complex [1]. The mentoring study takes educational and social characteristics into account when judging how well different language models personalize their answers [2]. AspireNextGen takes explicit skills, chosen interest domains, and optional free-text career intent, then normalizes them before making recommendations [8].

Overall, personalization is moving away from one-off questionnaires and toward a mix of structured profile data and contextual information from the user.

B. Interest-Based Personalization

Interest-based profiling is a second approach. Roy and Sharma build Holland's RIASEC model into their recommendation method [5], which gives a structured way to describe a user's interests across occupational

categories. Machine-learning models can then use these representations to suggest careers. This suggests that psychological interest models can work alongside purely skill-based methods rather than replace them.

C. Conversational Personalization

Conversational systems add another layer because users can describe their needs in their own words. AdaptJobRec judges how complex a query is and adjusts its processing accordingly, using memory, task decomposition, and recommendation tools only when a request needs them [1]. This reflects a shift from static recommendation toward interactive guidance.

V. AI-BASED CAREER RECOMMENDATION TECHNIQUES

The reviewed studies use a wide range of techniques. These include Decision Trees, XGBoost, Support Vector Machines, Naïve Bayes, Random Forest, neural networks, semantic similarity, natural language processing, large language models, recommendation systems, knowledge graphs, reinforcement-learning-based approaches, fuzzy logic, and Retrieval-Augmented Generation.

Shirtode et al. show that career recommendation research spans several categories: feature-based recommendation, personalized learning, predictive classification, job recommendation, skill-gap analysis, fuzzy logic, and ontology-based methods [4]. Patil et al. likewise find machine learning, NLP, recommendation systems, and LLM-based methods across different guidance applications [7].

This variety suggests there is no single best method. The right choice depends on the data available, the target population, the application's requirements, and how much personalization is needed.

VI. SKILL-GAP ANALYSIS AND PERSONALIZED LEARNING

Skill-gap analysis is one of the more meaningful developments in recent career recommendation. A basic system tells a user which career might suit them. A more useful one also tells them which skills they lack and what to learn next.

AspireNextGen does this by mapping roles to skills and comparing a user's current skills with those a recommended role requires [8]. AI NEWUS uses performance data to find weaknesses in technical, logical, verbal, and quantitative areas [3]. The survey by Shirtode et al. also names skill-gap analysis as an important research direction [4]. Together, these point to a gradual shift from predicting careers to supporting actual skill development.

VII. ADAPTIVE LEARNING AND PERFORMANCE ANALYSIS

AI NEWUS shows how career guidance can be tied to adaptive learning and assessment [3]. Its components include user profiling, course progression, dynamic question generation, aptitude assessment, technical preparation, company-specific preparation, AI mock interviews, feedback, and performance analytics. Performance data is used to guide progression and to flag areas that need work.

The notable point is that the system keeps using what the learner does, instead of relying only on details collected at registration. This can make career-development systems more responsive as a user's abilities change.

VIII. LARGE LANGUAGE MODELS AND AI MENTORING

Large language models have opened new options for conversational mentoring. Luo et al. evaluated GPT-4, LLaMA 3, and PaLM 2 for personalized mentoring in computing, combining quantitative NLP analysis with qualitative human evaluation [2].

Their findings indicate that language models can produce responses that reflect a user's background and professional situation. The study also underlines that human mentors still matter. LLMs may serve as scalable sources of information, feedback, and guidance, while people remain important where deeper context, judgement, or individual support is needed.

IX. AGENTIC AI FOR CAREER RECOMMENDATION

AdaptJobRec is a more advanced example of conversational career recommendation [1]. Its architecture has five parts: query-complexity identification, memory processing, task decomposition, personalized recommendation tools, and agent-based execution. For simple queries, the system picks a suitable tool directly. For complex ones, it processes relevant conversation history and breaks the task down before running the tools [1].

Evaluated on Walmart's real-world career recommendation scenarios, it reported up to a 53.3% reduction in average response latency compared with the competing approaches tested, along with better recommendation accuracy [1]. Agentic designs therefore look promising for complex conversational recommendation, though they are likely to be more demanding to build and run than simpler systems.

X. EXPLAINABLE AI AND TRANSPARENT RECOMMENDATIONS

Explainability matters in career guidance because the decisions involved can shape education, employment, and long-term professional paths. AspireNextGen uses a hybrid architecture that combines structured role-skill mapping with semantic similarity [8]. It keeps recommendation and explanation separate: structured data drives the recommendation, and controlled natural-language generation turns the result into readable guidance [8].

The architecture has four layers: user interaction, backend API, data, and AI processing. Normalized skills and role-skill relationships feed the system, and semantic similarity ranks the roles [8]. This responds to a common criticism of black-box recommenders, since users can get some sense of why a particular career was suggested.

XI. MULTILINGUAL AND CONTEXT-AWARE GUIDANCE

Guidance systems need to work for users from different linguistic backgrounds. Sankalp includes multilingual voice interaction in an architecture that also uses semantic matching, sentiment analysis, knowledge graphs, job-trend information, and adaptive recommendation [6].

It was evaluated on 160 participant profiles and reported a Top-1 Hit Rate of 77.5%, a Top-3 Hit Rate of 90.5%, a mean satisfaction score of 4.71 out of 5, and an average response time of 1.25 seconds [6]. These figures belong to Sankalp's own experimental setting and should not be compared directly with results from the other studies. Even so, multilingual and voice-based interaction is clearly an important way to make AI career guidance more accessible.

XII. INTEGRATION OF CAREER GUIDANCE FUNCTIONS

A problem that recurs across the literature is fragmentation. Different systems concentrate on different functions: career recommendation, skill assessment, learning recommendation, interview preparation, mentoring, skill-gap analysis, performance tracking, or job recommendation.

AI NEWUS tries to combine several of these in one platform [3], and the survey studies call for closer integration of career discovery, skill development, and preparation [4], [7]. Still, full integration remains an open research area.

A future career-development ecosystem could connect the whole path: profile, assessment, recommendation, skill gap, learning, practice, feedback, and career development. Doing so would narrow the divide between choosing a career and steadily building the skills for it.

XIII. COMPARATIVE ANALYSIS

Table II. Comparative Analysis of the Reviewed Studies

Aspect	Main Findings Across Literature
User Profiling	Skills, interests, education, goals, professional level, and intent are commonly used
Personalization	Increasingly based on several user characteristics rather than a single assessment
Career Recommendation	Implemented with ML, recommendation systems, semantic similarity, and hybrid approaches
Skill-Gap Analysis	Increasingly connected with career recommendation
Learning	Adaptive and personalized learning approaches are emerging
Conversational AI	LLMs enable natural-language career interaction
AI Mentoring	LLMs can provide personalized guidance

XIV. FUTURE RESEARCH DIRECTIONS

The reviewed studies point to several open problems that future work could address.

- **Continuous and adaptive personalization.** Most systems build a user profile once and rely on it. Only a few keep updating it from later interactions, performance, or changing goals [3]. Models that adjust as a learner's skills and interests develop would give more accurate and more lasting guidance.
- **Explainable recommendation.** Explainability has been explored in only a small part of the literature [8]. Future work could study how to present explanations so that users of different backgrounds can understand and act on them, and how to measure whether those explanations actually build trust.
- **Integrated learning pathways.** Career recommendation, skill-gap analysis, learning support, and practice are often handled by separate systems [4], [7]. Research is needed on how to connect them so that a recommended career leads to a clear, ordered learning path.

- **Feedback-driven improvement.** Few studies describe how user feedback and outcomes feed back into the recommendation process. Mechanisms that learn from what users accept, reject, or complete could make recommendations better over time.
- **Multilingual and accessible interaction** Work on multilingual and voice-based guidance is still limited [6]. Extending it to more languages, dialects, and user groups would make AI career guidance available to many more people.
- **Real-time career information.** Job roles and skill demands change quickly. Combining live labour-market and job-trend data with recommendation methods could keep guidance current [6].
- **Human-AI collaboration.** Mentoring research suggests that language models work best alongside human mentors, not in place of them [2]. How to divide the work between the two, and how to hand over between them, deserves further study.
- **Consistent evaluation.** The studies use different datasets, metrics, and participant groups, which makes comparison difficult. Shared benchmarks and evaluation frameworks that cover accuracy, satisfaction, explainability, and learning outcomes would help the field compare approaches fairly.

XV. LIMITATIONS OF THE REVIEW

This review has several limitations. First, it covers only eight studies, chosen because they represent major research directions, so it cannot claim to include all work in the area. Second, the selection was not a systematic search, and relevant studies may have been left out. Third, the studies differ in datasets, populations, methods, and metrics, so their reported results could not be pooled or compared statistically, and the review is mainly qualitative. Fourth, some of the studies are surveys and others report specific systems, and their evidence differs in depth and strength. Finally, the field moves quickly, especially in large language models, so newer work may extend or challenge the observations made here.

XVI. CONCLUSION

AI is changing how career guidance is delivered. The eight studies reviewed here show a move from static, questionnaire-based advice toward personalized, interactive, and skill-oriented support. Personalization now draws on skills, interests, education, goals, and performance.

Conversational and agentic systems make guidance more natural, and large language models show promise for scalable mentoring, though human input is still needed. Skill-gap analysis and adaptive learning connect recommendations to what a learner should do next, and explainable approaches respond to the need for transparency in decisions that affect people's futures.

Even so, the field is fragmented. Career recommendation, skill development, mentoring, and preparation are often handled separately, personalization is rarely continuous, and evaluation practices vary widely. Progress will likely depend on adaptive personalization, explainable recommendation, integrated learning pathways, feedback-driven design, multilingual access, real-time career data, and consistent evaluation. Addressing these areas would help AI-based career guidance become more useful, transparent, and accessible.

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