



A systematic review of skill-centric career guidance systems: Integrating knowledge graphs, skill decay tracking, and country-based salary sequence intelligence

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Abstract

With the rise of online learning sites, professional networking platforms, and hiring services, the demand for effective systems to support skill development and career advice is increasing. Skills are stored on different resources like e-learning platforms, code repositories and professional profiles. In recent years, personalization has been an active research field, and a personalized learning recommendation system, which recommends resources according to users' choices, has been developed. However, they have difficulty accommodating shifts in the labour market and are prone to creating negative employment mismatches and limited alternative career opportunities. The paper provides a comprehensive review of the research conducted across skill extraction, large language model (LLM)-based career guidance, knowledge graph construction, learning path recommendation, prerequisite modelling, and knowledge tracing, fairness and algorithmic bias in career AI, and country-based salary integration to improve adaptive career guidance. Almost 45 peer-reviewed articles from 2018 - 2026 were collated from key digital libraries. The review highlights progress in areas such as skill inference, learning path recommendations using graphs, knowledge tracing that considers forgetting, career matching, recommendations that explain themselves, and understanding salary trends at a country level, which is important for career planning systems. However, these solutions are not integrated and do not create a system for learning altogether. They don't consider the monetary aspects of paying for a career either. The review also proposes a series of skills and financial outcomes to help learners identify if they have the financial resources and location to pursue a career. It highlights the need for a platform to enable multi-platform skill extraction, tracking of skill decay, dynamic career paths, explainable AI skill recommendations, prerequisite modelling, and geographic salary return sequences.

Keywords: Career guidance, Dynamic career roadmaps, Knowledge graph, Skill decay, Return on skill investment

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Introduction

In a rapidly changing world, continuous learning is crucial for any professional (Acemoglu & Restrepo, 2020). The employment landscape is changing more rapidly than individuals can adapt to new jobs. Education/learning systems must provide individual learning experiences. Custom learning environments with new e-learning opportunities and open-source technology. They offer career guidance systems connected to the needs in the labour market and to personal learning opportunities (Du Plooy et al., 2024).

Most learner evidence exists on platforms such as professional networking sites, code repositories and/or university learning management systems such as LinkedIn, GitHub and LMS, respectively. This division may complicate the development of a "shared learner model" that can develop over time (Akkasi, 2024; Murthy et al., 2025). It is difficult to consistently represent skills needs, the order of skills acquisition, and the changing and uneven part that skills play for specific career paths in highly diverse labour-market data (Autor, 2019; OECD, 2023).

What is also not studied is the economic benefit of investing in skills, which can differ across regions particularly depending on the scarcity or surfeit of skills (International Labour Organization, 2024). While the economic context of a learner from Sri Lanka or Nigeria may differ from that of a learner in Germany and the USA, their salary limits, investment returns, and learning priorities may differ as well. Moreover, career recommendation algorithms were discovered to be perpetuating gender, racial, and socioeconomic bias (Kleinberg & Raghavan, 2021; Raghavan et al., 2020). Effective peer-to-peer mentorship is not only available, but it also does not exist in current platforms (Gehreke et al., 2024; Martinez & Kim, 2023).

One important gap in the research is on the economic productivity of investment in skills, which varies considerably by region (International Labour Organization, 2024). A learner in Sri Lanka or Nigeria may earn a lower wage, receive a lower ROI on their investment, or have a different priority in the sequencing of a skill pathway than a learner in Germany or the USA. There is also evidence of gender bias, racial bias, and socio-economic bias in career recommendation algorithms (Kleinberg & Raghavan, 2021; Raghavan et al., 2020) and there is no current peer-to-peer mentorship in platforms (Gehreke et al., 2024; Martinez & Kim, 2023).

The study is guided by four research questions (RQs), which define the specific purposes of the study. The first research question (RQ1) focuses on the methods for extracting and representing skills in skill-centred career guidance systems. The second research question (RQ2) examines the role that AI- and large language model (LLM)-based systems play in delivering personalised career guidance and learning-path recommendations. The third research question (RQ3) focuses on the extent to which current career guidance systems are able to address the issue of skill decay and monitor learners' knowledge over time. The fourth research question (RQ4) concerns the main challenges of algorithmic fairness, integration of peer-mentorship, and geographic salary intelligence in career-oriented artificial intelligence systems. The four questions are used to structure the scope of the systematic review reported in the subsequent sections.

Methodology

This research has been performed using a Systematic Literature Review (SLR) method in line with PRISMA guidelines. This can reduce selection bias and gather information on a variety of topics on skill-based career guidance, adaptive learning systems, and geographical wage intelligence. Zotero was used to manage and organise references and Comet app was used to analyse the research papers.

Search strategy

Literature sources were retrieved from IEEE Xplore, ACM Digital Library, ScienceDirect (Elsevier) SpringerLink and MDPI. New research was also considered, using arXiv as a triangulation source and Google Scholar as a source. In the salary dimension of the review the World Bank Open Data platform, labour statistics from the International Labour Organization (ILO) databases of salary and wage studies were consulted. The main literature review period was 2019 to 2025. Salary and wage references were taken from 2018 to 2025.

The data was gathered using a keyword-driven search method under the following categories: (i) skills acquisition (skill mining, skill extraction, and expertise inference); (ii) knowledge representation (knowledge graph, prerequisites modelling, and skill dependencies); (iii) recommendation pathways (adaptive learning, personal learning pathways, and career recommendations); (iv) tracking (skill decay and knowledge tracing); (v) explainability (explainable AI and explainable recommendations); and (vi) economic environment (salary intelligence).

Search Strings were applied to titles, abstracts and keywords. The developed search strings include:

- A = skill acquisition: "skill mining", "skill extraction", "skill identification"
- B = knowledge representation: "knowledge graph", "skill graph", ontology, "skill dependency", prerequisite
- C = recommendation pathways: "career recommendation", "job recommendation", "learning path", "personalized learning", "adaptive learning", "career guidance"
- D = temporal tracking: "skill decay", "knowledge tracing"
- E = economic environment: "salary prediction", "wage prediction", PPP, "Country based Salary"

Inclusion and exclusion criteria

The selection of the papers is based on the criteria described in Table 1. There has been remarkable progress over the last few years on adaptive learning technology, mass skill learning techniques and recommendation systems based on knowledge graphs. The literature review of the surveys has been conducted for the period of 2018-2025. In terms of salary and wage rates, references between 2018 and 2025 are preferred.

The comprehensive selection process is illustrated in Figure 1. The screening process consisted of four steps: Initially, 412 papers were identified, and 38 publications were identified as duplicates and/or overlapping records. Next, identification of potentially relevant records, title/abstract relevance and full-text eligibility as per Table 1. In the final phase, a total of 45 papers met the inclusion criteria and were included for qualitative synthesis and data extraction.

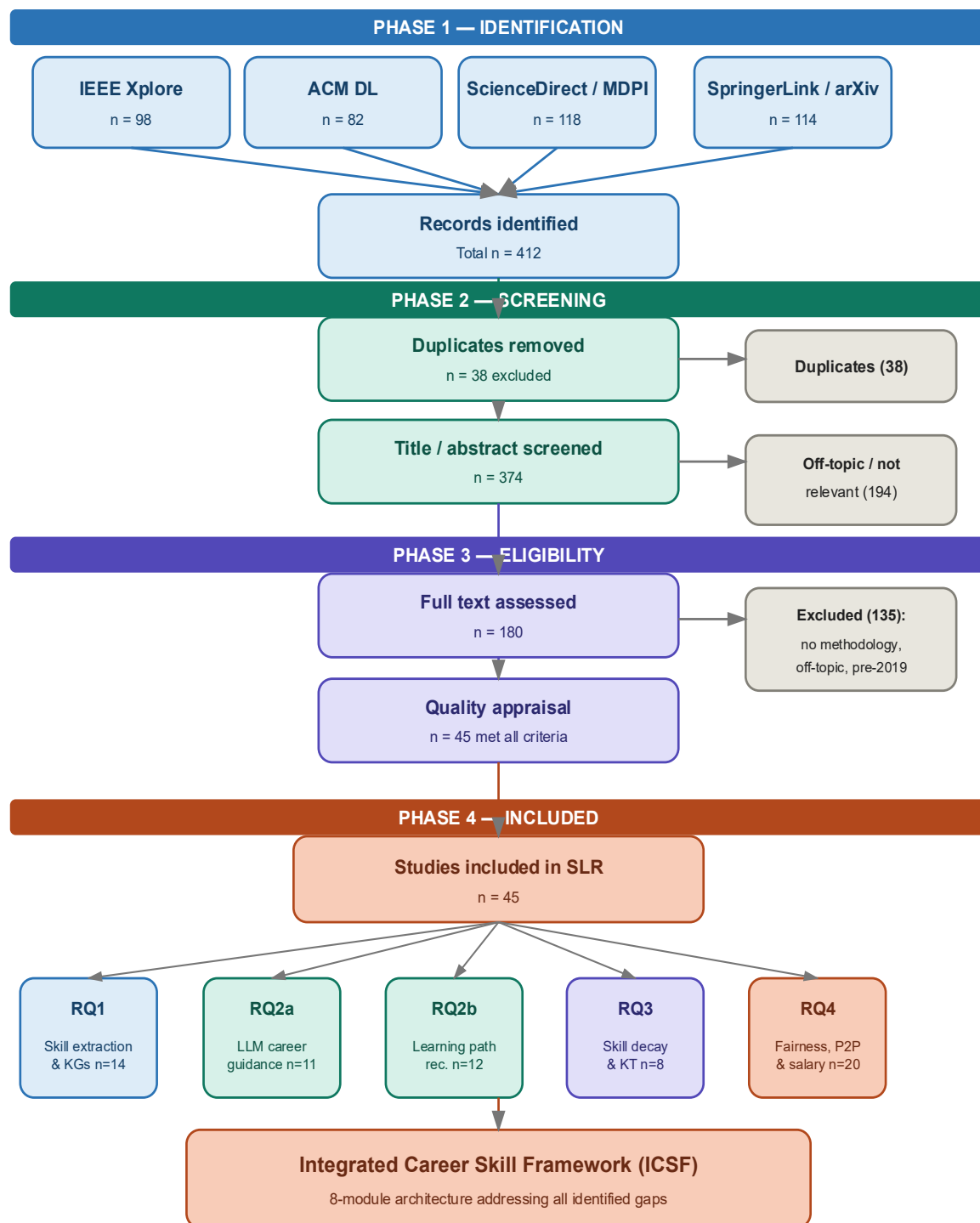


Figure 1. The PRISMA flow diagram which illustrates the systematic process of paper selection

Table 1: Inclusion and exclusion criteria for selecting papers

Inclusion criteria	Exclusion criteria
Published in academic paper or journal or conference article.	Any sources besides scholarly papers, journals, or books (website, blog, opinion piece, etc).
Contains information that pertains to at least one primary keyword theme.	Publication in a non-English language
Proposes a systematic model or an analytical framework.	Theoretical without a proposed methodological process.
A detailed methodology has been presented.	No relation to the keyword topics identified.
Published between 2019 and 2025 (salary and wage data: 2018–2025).	Re-publication from the same research group (duplicate or overlapping publications).

Results

The 45 reviewed references were thematically classified into five principal evidence domains as shown in Figure 2: AI/LLM guidance, fairness/peer/salary intelligence, skills acquisition, temporal tracing and decay, and knowledge representation. Fairness/peer/salary-related evidence represented the largest thematic group, followed by AI/LLM guidance, while temporal tracing/decay represented the smallest group. A summary of the findings from the addressed research questions is given in Table 2.

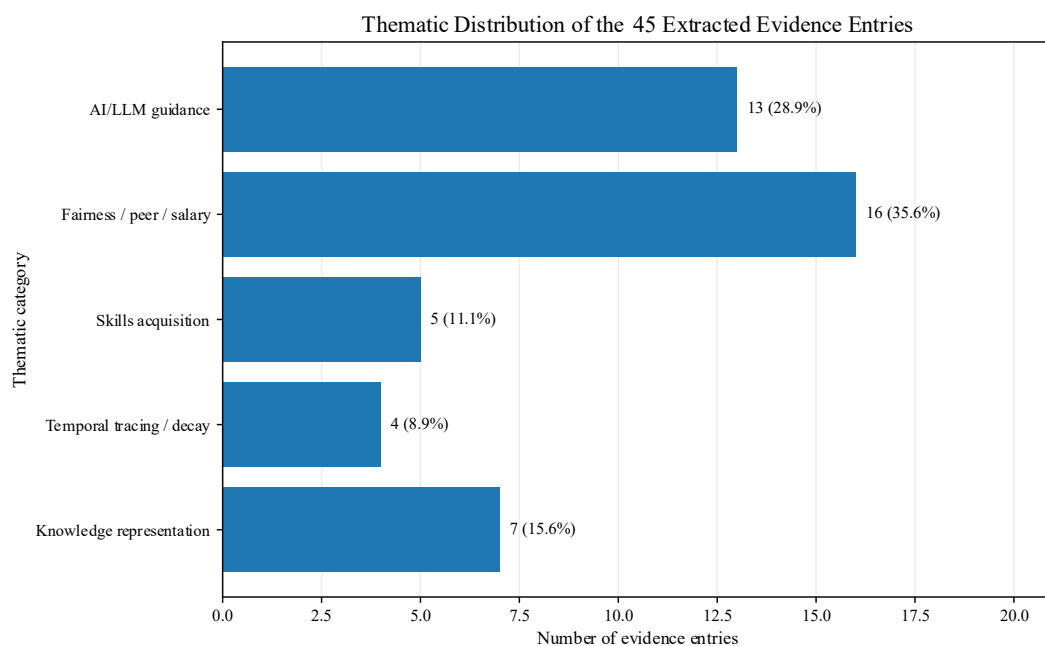
**Figure 2.** Thematic distribution of the 45 reviewed references across the five principal evidence domains

Table 2: A summary of the results of the research questions declared in the introduction
(Continued on next page)

Key Findings	Author(s)- references with data sources
RQ1: Skill Extraction and Knowledge Representation	
For the skill extraction task, transformer models (BERT, ESCO fine-tuned) achieve higher scores than the rule-based NLP models.	Akkasi (2024)-job description; Alonso et al. (2025)-job and O*NET data
Multilingual models perform exceptionally well in detecting skills across different languages.	Zhang et al. (2023)- Job-market text / taxonomy
The Jaccard similarity-based competency matching method is better than cosine similarity at capturing the overlaps in functional skills, especially for role adjacent competencies.	Saatçı et al. (2024)- Resumes
Dynamically updated job-skill knowledge graphs designed with job posting data significantly outperform static job-skill knowledge graph baselines for career recommendations, and can be enhanced with median salary metadata.	Seif et al. (2024) - Job postings / job-skill graph
In heterogeneous institutional systems, temporal graph structures are found to be more effective than snapshot-based graph structures in predicting next-skill acquisition in student-centric knowledge progression graph systems.	M.D. & Krishnamoorthy (2025)
In career-oriented settings, the most critical challenge has not yet been addressed: the ordering of prerequisites. Most systems only model the skill gaps in the current state of the system and do not model the evolution of skill acquisition.	Singla and Verma (2025); Zhang et al. (2022)
The combination of hybrid NLP and machine learning pipelines that are trained on annotated competency datasets can deliver good generalisation across a variety of job areas for resume classification.	Ali et al. (2022)
RQ2: AI and LLM-Based Career Guidance and Learning Path Recommendation	
GIRL (fine-tuned LLM with Reinforcement Learning) produces high-quality personalised job narratives from candidate CVs that beat non-personalised retrieval baselines.	Zheng et al. (2023) - Candidate CVs
LLMs are competitive career trajectory predictors, as the CAREER transformer model outperforms conventional econometric models in predicting job transitions and wages.	Vafa et al. (2024) - Large-scale employment data
In higher education, Generative AI tools offer tangible advantages such as customisation of learning, instant feedback, language support, and more, alongside documented challenges of bias, hallucination, and academic integrity issues.	Kutty et al. (2024)
Graph attention mechanism combined with deep reinforcement learning for learning path recommendation demonstrates significant improvements in path relevance and learner engagement.	Gu (2025)- Learner / learning-path data
The LLM-based path generation greatly enhances pedagogical coherence by leveraging real-time mastery state into the recommendation loop.	Zhang et al. (2025)- Mastery / learning data

Key Findings	Author(s)- references with data sources
Recommendation pathways with explicit prerequisite reasoning result in significantly higher engagement and completion rates of MOOC learners, thus establishing explainability as a direct path to learning outcomes.	Frej et al. (2024)- Learner engagement data
Personalised learning pathway tools have a positive impact on learner outcomes in all contexts and cultures, and AI-supported personalised support is not equally distributed across students.	Tapalova & Zhiyenbayeva (2022); Maphosa & Maphosa (2023)
RQ2: AI and LLM-Based Career Guidance and Learning Path Recommendation (<i>continued from previous page</i>)	
The knowledge graph recommendations generated by Uncertainty-weighted approaches are more successful than deterministic approaches in terms of both recommendation precision and user satisfaction for Job Education Knowledge Graph.	Fettach et al. (2024)
Training corpus bias consistently leads to an out-of-step alignment of digital skills frameworks for high-income labour markets with competence needs in South and South-East Asian economies.	Asian Development Bank & LinkedIn (2022)
RQ3: Skill Decay and Temporal Knowledge Tracing	
The LSTM-Informer hybrid models are more accurate in skill state predictions than ordinary baselines of Bayesian Knowledge Tracing and Dynamic Key-Value Memory Network when the inactivity period is more extended, as they directly model the long-range temporal dependence of forgetting skills.	Gao & Liu (2025)- Sequential learner data
Knowledge tracing models have been enhanced by making explicit models of learning and forgetting behaviour, as opposed to monotonic learning in the case of BKT.	Chen et al. (2022)- Knowledge-tracing sequences
Self-attention architectures with a cognitive framework embedded in them provide significant interpretability for predicting knowledge state transitions.	Pu et al. (2022)- Knowledge-tracing data
The performance gains of adaptive learning systems that take into account the temporal degradation of knowledge are evident when compared with systems that do not account for the permanency of knowledge.	Du Plooy et al. (2024)
A very important gap in career guidance systems that has not been dealt with is the automatic notification of learners when a previously mastered skill has fallen below a job-relevant threshold.	Markchom et al. (2025)
RQ4: Fairness, Peer Mentorship, and Geographic Salary Intelligence	
AI hiring systems, which learn from past data, reflect and amplify the same societal patterns as group-level disparities in gender, race, and socioeconomic status exist despite individual fairness constraints being in place.	Raghavan et al. (2020)- Historical hiring data Kleinberg & Raghavan (2021)
Even if the student population is not explicitly targeted in the code, LLM-based career systems are nationalistic, gendered, and biased against non-Western student groups, and Generative AI tools trained on Western corpora generally underperform for non-Western student groups.	Kotek et al. (2023); Kutty et al. (2024)
There are systematic algorithmic hiring differences due to gendered language in resumes, with adversarial de-biasing appearing promising but without fairness-aware career guidance in integrated systems literature.	Parasurama & Sedoc (2022); Beutel et al. (2017) – training representation

Key Findings	Author(s)- references with data sources
The effect of AI in skill recommendations in P2P learning networks yields significantly higher engagement and retention results than those of non-mediated peer pairing; cost and availability continue to be significant challenges in lower-income populations.	Martinez & Kim (2023)- Skill-learning network data Werntz et al. (2023)- Peer-mentor referral data
Geography is a significant moderator of the skill-wage dynamics, with software engineering salaries differing by a factor of 10-20× (nominal) and 2-5× (PPP adjusted) between high-income and low-income countries.	ILO (2024); World Bank (2024) - Labour and economic indicators
The direct transposability of models of skill valuation that are common in the West is confounded by the fact that returns to digital skills vary widely with sector context and infrastructure quality in developing countries.	Fietz & Lay (2023)
Furthermore, no existing career guidance system uses PPP adjusted, country-specific salary intelligence as a decision layer in the process of roadmap generation, which is especially significant for learners in developing economies.	Autor (2019); ADB & LinkedIn (2022)

RQ1: What are the methods of extracting and representing skills in skill-centred career guidance systems?

Skills extraction

To ensure personalized learning and career guidance, skills need to be harvested from a variety of sources including e-learning platforms, job opportunities, and others (Akkasi, 2024; Murthy et al., 2025). The first methods were rule-based and keyword matching, which were simple but lacked flexibility. In the modern era, machine learning and deep learning algorithms, particularly transformer-based algorithms, are increasingly capable of extracting skills from non-structured data, making them more efficient (Akkasi, 2024; Alonso et al., 2025). However, most current methods assume that skills are unchanging and do not deal with the problems of dependencies and temporalities. Furthermore, the effectiveness of skill extraction algorithms depends on the amount of information extracted, not how well they can be applied to writing individual career paths or learning plans.

Skills and career opportunities knowledge graph

There are various knowledge representations including the Skills Graph from LinkedIn (Alonso et al., 2025) and standard knowledge representations, such as ESCO taxonomy and O*NET (Fettach et al., 2024), that have been discussed in relation to skill knowledge. Such graph-based skill-to-job representations, based on KG methods, offer semantic grounding and inference capabilities for conducting gap analysis and providing explanations. The skill graphs available today are mostly taxonomic and not learning-driven prerequisite-based. Moreover, these skill graphs are mostly static in nature, unable to change dynamically as a learner acquires knowledge about a specific skill.

Prerequisite and skill dependency

Depending on skills is an important problem when it comes to building learning paths, so prerequisite modelling should be applied. In contemporary research, it has been managed to

automatically extract skills' relationships, based on learners' data, using statistical dependency analysis, graph neural networks, and variational autoencoders (Zhang et al., 2022). While effective and scalable, graph-based approaches have been shown to focus primarily on academic skills and have limited attention on the skills required for the workplace. Additionally, the temporal mastery tracking and work-level reasoning are typically ignored. For skills and competency mapping, Singla and Verma (2025) found seven significant challenges with job recommendation systems. Most of these systems have no prerequisite modelling and also have limited career-related reasoning and focus primarily on skill gap recognition. This is particularly problematic for the students who specialize in disciplines suffering from obsolescence of their skills, e.g., software engineering or data science. Deepa et al. (2024) demonstrated that using hard graph edges to explicitly represent prerequisite constraints in reinforcement learning for path recommendation leads to better learning efficiency compared to using soft preference weights.

RQ2: What is the role of AI and LLM-based systems in providing individual career guidance and learning path recommendations?

LLM-based career guidance and generative recommendation

Zheng et al. (2023) introduced GIRL, a model that can be fine-tuned with supervision and reinforced with learning to output tailored job descriptions from candidate CVs. Wu et al. (2023) took this idea further and added the LLMs and graph-based user behaviour information together using GLRec. Vafa et al. (2024) have proposed a transformer-based foundation model, trained on large datasets of resumes, that can accurately predict job transitions and wages better than traditional econometric models. Although these developments, LLM-based career systems have severe drawbacks as black-box systems with limited explanatory potential, computational complexity, and reliance on training sets that are heavily skewed to the Western labour market, making them not well suited to the context of labour markets in developing economies (Vafa et al., 2024; Kotek et al., 2023). The limits are similar to those identified in the extensive literature on GenAI in education. As previously noted, in the context of higher education, GenAI can offer a wealth of pedagogical advantages (Kutty et al. (2024), such as personalised learning, instant feedback, and administrative efficiency, but it comes with documented challenges like accuracy, bias, and integrity issues. The lessons that can be learned from career guidance systems are clear. An LLM-based career counsellor trained on biased occupational information should be equally vulnerable to being similarly protected as an LLM academic feedback tool, and should be: Auditable of the bias in the training data, Input output transparency features, Explainable outputs. Another study by the ADB and LinkedIn (2022) found that digital skills frameworks created mostly for high-productivity labour markets are never-aligned with the competency needs of South and South-East Asian economies.

Explainable recommendation systems

The ability to provide natural language explanations of recommendations in the form of path and prerequisite chain enables trust building and enhances transparency in KG-based recommendation systems (Markchom et al., 2025). Frej et al. (2024) found that MOOC learners who are engaged and will complete a course are significantly more likely when the recommendation pathways are given with explicit prerequisite reasoning, where they showed that explainability is a direct driver of learning outcomes. Most systems, however, focus on the

jobs or courses to recommend, and do not consider the skill preparation pathway or the effect of skill decay.

Personalised learning path recommendation

LPRs try to provide the learner with a suggested learning path, with personalisation usually being done through collaborative filtering, reinforcement learning, and knowledge graph methods (Zhou & Wang, 2025). There are two main disadvantages of the current methods – rigidity and lack of adaptability due to their fixed curriculum-based nature. The key property that makes reinforcement learning different from the others is flexibility. It is more suitable for modelling with prerequisite relations and more helpful to generate explainable paths than knowledge graphs are. However, there are several systems that are specifically developed for educational purposes, but without job requirement and skills evaluation. In order to improve the path relevance problem, Gu (2025) proposed a graph attention mechanism with deep reinforcement learning. Zhang et al. (2025) combined knowledge tracing with LLM-based path generation, concluding that adding mastery state significantly enhances pedagogical coherence. Tapalova and Zhiyenbayeva (2022) concluded that personalised learning pathway (PLP) tools have a consistent positive effect on learner outcomes in different institutional settings. Zhong (2023) has demonstrated that customized higher education learning environments result in statistically significant learning gains and retention. Many systems are developed for educational settings and do not necessarily connect with external job requirements and real-world skill valuation (Maphosa & Maphosa, 2023).

RQ3: What are the approaches taken in career systems to address skill decay and tracing temporal knowledge?

Skill tracing, decay, and knowledge tracing

Knowledge tracing (KT) models are used to measure knowledge of a learner over time and based on the sequence of interactions (Markchom et al., 2025). Moderately newer models take into account forgetting and decay over time (Gao & Liu, 2025; Pu et al., 2022), while older models such as Bayesian Knowledge Tracing (BKT) assume monotonic learning. In predicting skill state over long inactivity periods, LSTM-Informer hybrid architectures were shown to significantly outperform the standard baseline models (BKT and Dynamic Key-Value Memory Network) by Gao and Liu (2025). Chen et al. (2022) proposed a knowledge tracing model explicitly incorporating learning and forgetting behaviour. Pu et al. (2022) have integrated a cognitive model into self-attention models to improve interpretability in predicting knowledge state transitions significantly. A scoping review by Du Plooy et al. (2024) established that adaptive learning systems that include temporal knowledge degradation can be correlated with measurable results in learner performance outcomes. Kutty et al. (2024) highlight that, whereas AI technologies deliver real-time personalised feedback, they fail to monitor the long-term direction of student learning, highlighting the disconnect already discussed in the KT literature. An important gap in career guidance applications that was not addressed in the reviewed systems is the lack of automatic learning alerts if a previously mastered skill has decayed below a job-relevant level.

RQ4: What are the key challenges in algorithmic fairness, peer mentorship integration and geographic salary intelligence in career AI?

Fairness and algorithmic bias in career AI

One of the most burning topics regarding career guidance and recruitment AI nowadays is bias in algorithms. As mentioned by Raghavan et al. (2020), the AI model built on the historical data set of hiring practices reproduces and amplifies the existing societal biases according to gender, skin colour, and social classes. While all of the individual criteria of fairness are satisfied, Kleinberg and Raghavan (2021) mathematically show that the AI can generate systemic inequity in terms of the suggestion of skilful employment. The role of gender discrimination in CVs was identified by Parasurama and Sedoc (2022). In modern LLM-powered career guidance systems, for instance, it was demonstrated that the geographical bias in the GPT-based recommendations is influenced even if users include geographical information in their prompts (Kotek et al., 2023). Adversarial fair learning led to the reduction of gender pay gap in recommendation job AI (Beutel et al., 2017). To date, no research has been conducted on how to develop career guidance that includes a bias-reduction function.

Peer-to-peer skill marketplaces and digital mentorship

Peer mentoring has been shown to improve academic integration, career confidence, and career success, among other outcomes, and has been tried and tested multiple times (Gehreke et al., 2024). Martinez & Kim (2023) found that AI skill recommendation shows higher engagement and knowledge retention results than unmediated peer pairing in P2P learning networks. Sri et al. (2025) also demonstrated that the use of deep learning to recommend personalised learning paths in a skill exchange network enhances the effectiveness of the peer match recommendations and the efficiency of skill acquisition. Yet, the current career guidance platforms lack an authenticated, structured peer-to-peer market of skills and local-geographic skills filtering and no pricing in local-currency, which is a critical access gap for learners in economies where international mentorship platforms are too expensive for them (Werntz et al., 2023).

Country-based salary sequence integration

One of the reasons career guidance is different from types of guidance is that career guidance does not always focus on salary rates in the country. The way regions affect skill development can be quite different. The International Labour Organization (2024) shows that salary limits and the cost share for skills vary a lot between countries. The main point is that a career pathway might seem like a choice for a learner, but it might not make sense if the learner believes the salary will not be enough. When it comes to salaries software engineers can earn ten to twenty times more in high-income countries compared to low-income countries. When looking at purchasing power parity (PPP) the difference is still significant two to five times (International Labour Organization, 2024). According to Autor (2019) the geographic dimension becomes important in the link between skill wages because the location of digital skill premiums matters. The proposed Country Based Salary Sequence Integration Framework would include a Country Based Salary Sequence Metadata Layer (SML). This layer would take into account purchasing power parity for each step along the learner's career path. The system would calculate a path score to determine the return

for the learner in the learner's environment using an ROI-weighting formula. It would also adjust the learning path while skills are being acquired to make sure the learner gets the return. The outcomes are a -criteria optimization, feasibility based on prerequisites relevance, to the job market and geographic economic return.

These findings motivated an implementation of an Integrated Career Skill Framework (ICSF) to address the gaps revealed in all four research questions. The ICSF is discussed later in this review. Figure 3 summarises the number of distinct reviewed references associated with each proposed ICSF module. The highest coverage is observed for LLM-based career guidance and the Country-Based Salary Sequence Layer, followed by the Dynamic Career Knowledge Graph.

Discussion

One of the reasons career guidance is different from types of guidance is that career guidance does not always focus on salary rates in the country. The effect of regions on skill development is different. The International Labour Organization (2024) shows that salary limits and the cost share for skills vary greatly between countries. The point is that a career pathway might seem like a choice for a learner, but it could not make sense financially if the learner believes the salary will not be enough. In terms of salaries software engineers can earn ten to twenty times more in high-income countries than in low-income countries. When looking at purchasing power parity (PPP) the difference is two to five times (International Labour Organization, 2024). According to Autor (2019) the geographic dimension becomes important in the connection between skill wages because where digital skills are located matters. The proposed Country Based Salary Sequence Integration Framework would include a Country Based Salary Sequence Metadata Layer (SML). This layer would consider purchasing power parity for each step along the learner's career path. The system would calculate a path score to determine the return for the learner in the learner's environment using an ROI-weighting formula. It would also adjust the learning path while skills are being acquired to ensure the learner gets the return. The outcomes are a criteria optimization, feasibility based on prerequisites relevance, to the job market and geographic economic return.

The review addresses RQ1 by stating that the skill extraction for NLP with transformers and ontology construction has progressed (Akkasi, 2024; Alonso et al., 2025); yet skills do not change and are disconnected from career pathways. No reviewed system exists that tracks over-time skill proficiency development and informs learners about outdated skills relative to the skill requirements in the labour market (Singla & Verma, 2025).

To address the question of RQ2, LLM-based career guidance systems like GIRL (Zheng et al., 2023) and CAREER (Vafa et al., 2024), which offer the possibility of a generative personalised career narrative, but are limited by a bias towards the western corpus, lack of explainability, and high computational costs. Reinforcement learning-based learning path recommenders (Gu, 2025; Zhou & Wang, 2025) perform well in terms of pedagogical performance, while few of them incorporate real-time information from the job market.

The review addresses RQ3, verifying that although there has been some work on skill decay models like LSTM-Informer (Gao & Liu, 2025) and forgetting-aware extensions of BKT (Chen et al., 2022), these models are not linked to actionable career guidance. None of the systems reviewed offer proactive notifications and dynamically update career roadmaps based on the identified skills obsolescence.

The findings for RQ4 indicate that the three gaps that were highlighted by the reviewed systems have not been filled. First, there are not yet any peer-to-peer mentorship platforms in the literature that offer an affordable, local-currency pricing model as well as a verified identity for the mentor, which leaves learners in less privileged contexts without a trusted and financially viable path to mentorship. Second, what constitutes a fair system and what constitutes an economic optimisation are treated as distinct problems: the systems that try to reduce the bias in recommendations do not attempt at the same time to optimise for a learner's financial return, and the systems that attempt to optimise for a financial return rarely try to check whether that optimisation is fair across the demographic groups. Third and most important, none of the career guidance systems includes country-specific salary intelligence in purchasing-power-parity (PPP) adjusted format in career decisions. This is important because the financial return on the same amount of investment in a similar skill is not the same across countries: for instance, one learner in Sri Lanka might see a very different return from a specific skill pathway compared to another learner in Germany or the United States, and existing systems are largely based on assumptions derived from Western labour markets.

Although there have been significant advances in skill extraction with NLP and machine-learning classifiers, particularly transformer-based models, that improve the accuracy of skill acquisition from text-based and activity-based data streams, there has been no improvement in the literature with regard to skills of low market value (Akkasi, 2024; Alonso et al., 2025; Murthy et al., 2025). Knowledge-graph approaches (which are based on embeddings, large-scale graphs and ontologies) offer a structured description of the relationship between skills, jobs and occupations, but are not often used to represent skills that the individual learner has actually developed (Fettach et al., 2024; Seif et al., 2024; Wasi, 2024). Prerequisite and skill-dependency modelling, employing graph neural networks, graph autoencoders and optimisation methods, has been explored in related work, which automated the prerequisite and dependency relationship between skills and concepts, but provides partial support for learners who are not targeting a similar family of jobs. Using transformers and recurrent neural networks to predict forgetting and relearning with a Bayesian model can be effective (Chen et al., 2022; Gao & Liu, 2025; Du Plooy et al., 2024), although the predictions have been internal processes of the modelling system and not regularly brought back to the learner as feedback for action. Despite some good results, however, fairness-oriented work has been successful in reducing gender and location-based bias in recommendations, albeit so far with limited application because of the scarcity of labour-market data and slow moving wage information in many developing countries, and not yet integrated with career pathway optimisation at system level (Beutel et al., 2017; Kleinberg & Raghavan, 2021; Parasurama & Sedoc, 2022; Raghavan et al., 2020). Although country-based salary-sequence integration relies on ILO and World Bank salary data, as well as tri-objective optimisation based on prerequisite feasibility, job relevance and geographic ROI, it also faces issues of low availability of data in developing economies and a lag between salary change and changes in labour demand (Fietz & Lay, 2023; International Labour Organization, 2024; World Bank, 2024). There is generally low transparency in career-AI decision-making (Kotek et al.,

2023; Zheng et al., 2023; Vafa et al., 2024), though there are some efforts in explainability research, such as attention-based path reasoning, natural-language explanation generation, and generation of skill roadmaps, featuring prerequisite chains, salary projections, and fairness scores. Finally, the development of peer-to-peer skill marketplaces, where universities' identities are verified, and AI tools are developed for skill matching, with APIs for geolocation functionality, shows the potential for connecting verified peer mentors to peer-to-peer pricing and location-based filtering, though no affordable, and university verified, peer-to-peer mentorship marketplaces exist (Gehreke et al., 2024; Martinez & Kim, 2023; Sri et al., 2025; Werntz et al., 2023).

Future research priorities involve the development of (i) country-aware salary sequence models as optimisation layers in career roadmap engines, using cross-country, skill-disaggregated salary databases from ILO, World Bank, and real-time job posting data; (ii) federated approaches to continuously enhance salary intelligence without compromising the quality or confidentiality of labour market data; (iii) multi-objective optimisation frameworks, which take into account prerequisite feasibility, job market relevance, geographical economic return, and demographic fairness; and (iv) ethical safeguards to ensure that salary-aware systems do not inadvertently deter learners in lower-income economies from career paths that are potentially ambitious or socially useful. The ICSF is proposed to be immediately moved forward to be empirically validated with a prototype implementation in a Sri Lankan university context, based on the salary ranges of the ICTA and SLASSCOM.

This paper introduces an Integrated Career Skill Framework (ICSF) to address the gaps revealed in all four research questions. The ICSF is an eight-module platform architecture that can connect various skill extraction from multiple platforms, dynamic career knowledge graphs, skill decay trace, LLM-based career guidance, country-contextualised salary sequencing, fairness-aware algorithms, explainable recommendation interfaces, and university-verified p2p mentorship into a single learner-centred solution. The Integrated Career Skill Framework (ICSF) is an architecture that was proposed by the authors and consists of eight modules designed to implement the integration gaps identified during the evaluation of the RQ1–RQ4.

The design of the proposed Integrated Career Skill Framework (ICSF) is directly based on the gaps identified across the review. Research on skill extraction using transformers demonstrates that skill acquisition can be accurately identified based on text and activity data, but is not consistently associated with the proficiency level of a learner, the heterogeneity of the data sources, or how the learner's proficiency changes over time (Akkasi, 2024; Alonso et al., 2025; Murthy et al., 2025), highlighting the need for the Multi-source Skill Extraction module to construct a single skill profile for a learner from multiple, heterogeneous data sources. Skills, occupations and jobs can be linked via structured representations, though many knowledge graphs are static or not designed with the individual learner in mind (Fettach et al., 2024; Seif et al., 2024), and the Dynamic Career Knowledge Graph meets this requirement by depicting dynamic relationships between the learner, skills and target occupations.

Prerequisite modelling studies are used to model dependencies between skills and concepts, but these dependencies are not always linked to career roadmaps; the Prerequisite and Skill Dependency module is implemented to ensure prerequisite feasibility during pathway generation. While knowledge-tracing research models learning and forgetting over time, it rarely

relates those predictions to actual career actions, and the Skill Tracing and Decay module aims to track a learner's skill state on a continuous basis and update a roadmap when that skill state decreases.

The LLM-based Career Guidance module produces personalized guidance based on evidence related to the learner and their career, rather than just on unconstrained generation of guidance (Gu, 2025; Zheng et al., 2023; Vafa et al., 2024; Zhou & Wang, 2025). Country- and PPP-aware economic information is not well integrated into pathway decisions, but the Country Based Salary Sequence Layer takes socioeconomic information into the pathway optimisation directly.

Fairness research has consistently shown bias in algorithmic recommendation and hiring systems, (Beutel et al., 2017; Kleinberg & Raghavan, 2021; Parasurama & Sedoc, 2022; Raghavan et al., 2020), which is the motivation behind the Fairness and Bias Mitigation Layer, which applies fairness constraints and bias monitoring throughout the framework, not as an afterthought. Last, explainability and peer-learning research highlights the importance of transparency in reasoning and structured peer interaction (Gehreke et al., 2024; Kotek et al., 2023; Martinez & Kim, 2023; Werntz et al., 2023) these skills are then designed to operate separately, with the proposed Explainable Recommendation Interface and P2P Skill Marketplace module as complementary and integrated components of the ICSF architecture.

The central innovation of the ICSF is the Country Based Salary Sequence Layer, which is an operationalisation of a tri-objective optimisation model, balancing the following three elements: prerequisite feasibility (respecting skill dependency ordering identified from knowledge graph analysis); job market relevance (alignment with ESCO and O*NET occupational standards, with real-time job posting data); and geographic economic return (maximising the LKR or local-currency financial return per skill node, through a country context, using PPP-adjusted ILO, World Bank, and ICTA/SLASSCOM salary data (International Labour Organization, 2024; World Bank, 2024). A salary metadata layer is associated with each node in a learner's career roadmap, which is built on data from country-specific wage databases that have been adjusted for PPP, allowing the system to dynamically reorder the sequence of the skills being acquired to maximise the financial benefit, while meeting requirements for prerequisite and job market constraints.

The main challenges to implementing the ICSF are sparse salary data for many roles in developing economies, outdated market data (the salary databases typically lag 12-24 months behind market data), lack of alignment between the country-based job market taxonomy and the universal taxonomy (such as ESCO or O*NET), and ethical concerns (salary-based optimisation may discourage learners in lower earning economies from taking on ambitious career paths if the salary ceiling is lower than that of other paths). When trying to build up the salary data across institutions, federated learning approaches could mitigate data privacy issues.

Conclusions

In this paper, a systematic review of skill-centric career guidance systems is provided considering the following ten dimensions: skill extraction; LLM-based career guidance; knowledge graph modelling; learning path recommendation; prerequisite modelling; knowledge tracing and skill decay; explainable recommendation systems; peer-to-peer skill marketplaces; fairness and bias

in career AI; and country-based salary sequence integration. In particular, there has been much advancement achieved in automated skill extraction, knowledge representation, and prerequisite modelling. They are not, however, integrated and connected, nor do they consider that skills evolve, or they fail to consider practical job demands. Moreover, due to the neglect of the geographical economic dimension, existing career guidance systems cannot offer the information that is needed to account for the financial return of the investment in some skills. This review identifies the following gaps across all four research questions which the Integrated Career Skill Framework (ICSF) proposed in this review aims to address by bringing together 8 functional modules into a single platform for the learner. The Country Based Salary Sequence Layer is one of the ICSF's most important innovations, as it allows career guidance systems to shift from the instruction of what and how to learn to the advice of what is worth learning in a particular country's economic context, based on PPP adjusted salary information linked to country specific labour market conditions. The review recommends that future studies focus on creating geospatially aware, economically driven and equity-oriented career roadmap engines that are equitable for all learners, and that the ICSF be empirically tested as a first step.

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Conflict of interest statement

The author declares no conflict of interest.

Data availability statement

This study is a systematic review of the literature that examines publicly available and peer-reviewed sources. No primary dataset was developed or analyzed for this review. All reviewed sources are cited in the reference list.

Author Contribution

Conceptualisation and study design: S.H.P., W.G.; review methodology development and keyword strategy: S.H.P.; literature search, screening and inclusion/exclusion evaluation: S.H.P.; data extraction and thematic synthesis: S.H.P.; Country-Based Salary Sequence Integration Framework development: S.H.P.; fairness and bias section: S.H.P.; peer-to-peer marketplace section: S.H.P.; writing original draft preparation: S.H.P.; writing reviewing and editing: W.G., D.M.T.R.D.; supervision: W.G., D.M.T.R.D.; project administration: D.M.T.R.D. Key: S.H.P. = Serini H.

Puwakgolla; W.G. = Dr. W. Gunathilake; D.M.T.R.D. = D.M.T.R. Disanayaka. All authors reviewed the findings and approved the final version for submission.

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