International Journal for Educational and Vocational Guidance
https://doi.org/10.1007/s10775-026-09807-0

Artificial intelligence applications supporting women's career development: a scoping review

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Received: 13 August 2025 / Accepted: 25 April 2026

Abstract
Artificial intelligence (AI) is increasingly integrated into career guidance and organisational decision systems, yet empirical evidence on applications designed to support women's career development remains limited. Following the PRISMA extension for scoping reviews (PRISMA-ScR) and a preregistered protocol, we searched seven databases (plus backward and forward citation searching) and synthesised 13 empirical studies published between 2018 and 2025. Using inductive thematic analysis, we identified three functional domains: (1) bias mitigation and representation (e.g. auditing gendered language and platform-level disparities), (2) skills development and empowerment (e.g. AI-supported learning and writing interventions) and (3) career pathways and retention (e.g. matching and attrition-risk modelling). The evidence base was concentrated in system-facing applications that detect or shape inequities within recruitment, evaluation and exposure systems; fewer studies evaluated individual-facing developmental support, and sustained career outcomes were rarely measured. Formal theory use was limited, with only a small minority of studies explicitly drawing on established frameworks; reporting on ethics, transparency and governance was inconsistent. We suggest that research prioritises longitudinal and theory-informed evaluations, including intersectionality-informed analyses, and assess downstream impacts on women's career trajectories alongside robust governance and accountability practices.

Keywords Artificial intelligence · Career development · Gender equity

Résumé
L'intelligence artificielle (IA) est de plus en plus intégrée aux systèmes d'orientation professionnelle et de décision organisationnelle, mais les données empiriques concernant les applications conçues pour soutenir le développement de carrière des femmes demeurent limitées. En suivant la méthode PRISMA-ScR et un protocole préenregistré, nous avons interrogé 7 bases de données (ainsi qu'effectué une recherche de citations ascendante et descendante) et synthétisé 13 études empiriques publiées en-

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Published online: 04 June 2026

tre 2018 et 2025. À l'aide d'une analyse thématique inductive, nous avons identifié trois domaines fonctionnels : (a) atténuation des biais et représentation (par exemple, audit du langage genré et disparités au niveau des plateformes), (b) développement des compétences et autonomisation (par exemple, interventions d'apprentissage et de rédaction assistées par l'IA), et (c) parcours professionnels et rétention (par exemple, appariement et modélisation du risque d'attrition). Les preuves étaient principalement concentrées sur des applications orientées vers les systèmes, visant à détecter ou à façonner les inégalités au sein des processus de recrutement, d'évaluation et d'exposition ; peu d'études évaluaient le soutien au développement individuel, et les résultats de carrière à long terme étaient rarement mesurés. Le recours à des cadres théoriques formels était limité, seule une minorité d'études s'appuyant explicitement sur des modèles établis ; la transparence, l'éthique et la gouvernance étaient rapportées de manière inégale. Nous suggérons que la recherche privilégie des évaluations longitudinales et fondées sur la théorie, incluant des analyses tenant compte de l'intersectionnalité, et évalue les impacts à long terme sur les trajectoires professionnelles des femmes, parallèlement à des pratiques de gouvernance et de responsabilité rigoureuses.

Zusammenfassung
Künstliche Intelligenz (KI) wird zunehmend in die Berufsberatung und in organisationale Entscheidungssysteme integriert; dennoch ist die empirische Evidenz zu Anwendungen, die speziell die berufliche Entwicklung von Frauen unterstützen sollen, weiterhin begrenzt. Unter Anwendung von PRISMA-ScR und einem vorab registrierten Protokoll wurden sieben Datenbanken (zuzüglich Rückwärts- und Vorwärtssuche von Zitierungen) durchsucht und 13 empirische Studien aus den Jahren 2018 bis 2025 zusammengeführt. Mittels induktiver thematischer Analyse wurden drei funktionale Bereiche identifiziert: (a) Bias-Minderung und Repräsentation (z. B. die Analyse geschlechtsspezifischer Sprache und plattformbezogener Ungleichheiten), (b) Kompetenzentwicklung und Empowerment (z. B. durch KI-gestützte Lern- und Schreibinterventionen) und (c) Karrierepfade und Verbleib (z. B. Matching- und Attritionsrisikomodelle). Die Evidenzbasis konzentrierte sich auf systemorientierte Anwendungen, die Ungleichheiten in Rekrutierungs-, Bewertungs- und Expositionssystemen erkennen oder beeinflussen; weniger Studien untersuchten entwicklungsbezogene Unterstützung auf individueller Ebene, und nachhaltige Karriereergebnisse wurden selten gemessen. Der Einsatz formaler Theorien war begrenzt; nur eine kleine Minderheit der Studien bezog sich ausdrücklich auf etablierte theoretische Rahmenwerke. Zudem war die Berichterstattung zu Ethik, Transparenz und Governance uneinheitlich. Es wird empfohlen, dass die Forschung verstärkt langfristige und theoriegeleitete Evaluationen priorisiert, einschließlich intersektionaler Analysen, und die nachgelagerten Auswirkungen auf die Karriereverläufe von Frauen im Zusammenspiel mit robusten Governance- und Rechenschaftspraktiken untersucht.

Resumen
La inteligencia artificial (IA) se integra cada vez más en la orientación profesional y en los sistemas de toma de decisiones organizacionales; sin embargo, la eviden-

cia empírica sobre aplicaciones diseñadas para apoyar el desarrollo profesional de las mujeres sigue siendo limitada. Siguiendo PRISMA-ScR y un protocolo preregistrado, se realizaron búsquedas en siete bases de datos (además de búsquedas de citas hacia atrás y hacia adelante) y se sintetizaron 13 estudios empíricos publicados entre 2018 y 2025. Mediante un análisis temático inductivo, se identificaron tres dominios funcionales: (a) mitigación de sesgos y representación (por ejemplo, auditoría del lenguaje con sesgo de género y de las desigualdades a nivel de plataforma), (b) desarrollo de habilidades y empoderamiento (por ejemplo, intervenciones de aprendizaje y escritura apoyadas por IA), y (c) trayectorias profesionales y retención (por ejemplo, modelos de emparejamiento y de riesgo de abandono). La base de evidencia se concentró en aplicaciones orientadas a sistemas que detectan o moldean desigualdades dentro de los sistemas de reclutamiento, evaluación y exposición; menos estudios evaluaron el apoyo al desarrollo a nivel individual, y los resultados profesionales sostenidos rara vez se midieron. El uso de teoría formal fue limitado, con solo una pequeña minoría de estudios que recurren explícitamente a marcos teóricos establecidos; la información sobre ética, transparencia y gobernanza fue inconsistente. Se sugiere que la investigación priorice evaluaciones longitudinales e informadas por la teoría, incluyendo análisis basados en la interseccionalidad, y que evalúe los impactos posteriores en las trayectorias profesionales de las mujeres junto con prácticas sólidas de gobernanza y rendición de cuentas.

Introduction

Women's participation and advancement in male-dominated industries, particularly in science, technology, engineering and mathematics (STEM), continues to be constrained by systemic and intersectional barriers embedded within organisational, cultural and economic structures (Bapna & Funk, 2020; Trauth, 2006). Persistent challenges, including implicit bias, exclusionary work environments, unequal access to mentorship and professional development and the scarcity of visible role models, contribute to gendered disparities in career progression (Babalola et al., 2024). These barriers shape not only access and advancement but also women's sense of belonging, career decisiveness and long-term engagement in male-dominated professional contexts (Khan et al., 2024; Trauth, 2006).

Efforts to advance gender equity in career development led to targeted interventions such as upskilling initiatives, networking opportunities, sponsorship schemes and coaching and mentoring programmes (Brown & Lent, 2020; Ibarra et al., 2010; Maree & Nortjé, 2023; Saffie-Robertson, 2020). While foundational, such approaches can be constrained by resource demands, uneven geographic access and challenges of scalability and sustainability (Bapna & Funk, 2020; Terblanche et al., 2022). These limitations have intensified interest in whether technology-enabled supports can extend access to guidance and development opportunities.

In response, there is an increasing global attention to the potential of artificial intelligence (AI) technologies in overcoming such structural barriers and transforming the landscape of career support (Ding, 2024; Lent, 2025). AI systems, particularly those leveraging machine learning (ML), natural language processing (NLP) and generative AI (GenAI) models, are being integrated into a wide range of career development tools, from automated résumé feedback and personalised job matching to intelligent mentoring systems and communication coaching applications (Bommasani et al., 2021; Mer, 2023). These technologies offer the promise of scalable, personalised and data-informed support mechanisms that transcend the limitations of traditional human-led interventions (Yan et al., 2024). The emergence of GenAI powered by large language models (LLMs) is of particular relevance, as it can simulate professional scenarios, generate tailored feedback and provide context-sensitive career guidance (Ding, 2024). Such tools hold considerable potential for democratising access to career development resources, particularly among women who face systemic exclusions from elite professional networks or high-stakes mentoring opportunities (Duan & Wu, 2024; Gedrimiene et al., 2024).

Despite these technological advancements, empirical investigations into the effectiveness, equity implications and experiential outcomes of AI-driven career interventions remain nascent and uneven. Much of current literature is conceptual or speculative, with relatively few studies empirically examining how AI systems shape women's career-related outcomes, agency or experiences across contexts (Pasha, 2024; Tariq, 2025; Wang et al., 2021). This gap is particularly consequential given the accelerating adoption of AI tools by educational institutions, employers and governments for career guidance and employment-related decision-making (Manganello et al., 2025). Without clearer empirical understanding, AI systems risk reproducing and amplifying gendered disparities through biased data, opaque decision rules or optimisation objectives that prioritise efficiency over equity (Dastin, 2022).

This review draws on the Systems Theory Framework (STF) to conceptualise career development as shaped by interacting influences across individual, social, organisational and socio-economic systems (Patton & McMahon, 2006). In parallel, Social Cognitive Career Theory (SCCT) is used to interpret individual-level career outcomes, including self-efficacy, outcome expectations, goals and perceived supports and barriers (Brown & Lent, 2023). Together, STF and SCCT situate AI as both a system-level influence on opportunity structures and a potential contributor to individual career-development processes.

Accordingly, this scoping review systematically maps the emerging empirical literature on AI-enabled applications aimed at supporting women's career development. Anchored in the PRISMA extension for scoping reviews (PRISMA-ScR) guidance (Tricco et al., 2018), the review synthesises empirical studies published between 2018 and 2025 to (1) identify the types of AI-enabled applications being used; (2) examine the theoretical models underpinning these applications (where specified); (3) assess reported career-related outcomes; and (4) analyse ethical, practical and technological challenges and risks associated with deployment.

This inquiry contributes to the evidence base on AI and career development with direct relevance to educational and vocational guidance practice, organisational career support and policy contexts where gender equity remains a critical concern. It also aligns with the United Nations Sustainable Development Goals (SDGs), particularly SDG 5 (gender equality) and SDG 8 (decent work and inclusive economic growth) (United Nations, 2015). By clarifying how AI is being used and what outcomes and risks are currently evidenced, this review informs the development of more equitable career guidance systems and responsible AI-enabled career support.

Objectives

This scoping review aims to systematically map and synthesise the existing empirical research on AI-enabled applications designed to support women's career development. The specific objectives are to:

- Identify the types of AI-based technologies and applications currently employed to facilitate women's career development;
- Examine the theoretical frameworks and conceptual models underpinning these interventions;
- Assess the career-related outcomes associated with AI-driven approaches;
- Analyse the ethical, practical and technological challenges and risks linked to the deployment of AI in this context.

Analytic approach

To guide the synthesis and interpretation of an emergent evidence base, the review adopted an a priori analytic approach that (1) examined whether empirical work clustered in system-facing versus individual-facing interventions; (2) distinguished proximal outcomes from sustained career outcomes; and (3) mapped the extent to which studies were theory-informed and addressed ethics/governance.

This review provides an overview of how AI technologies are being leveraged to support women's career development and identifies gaps to inform future research and innovation.

Methods

Study design

This scoping review was conducted in accordance with the PRISMA-ScR guidelines, which provide a structured framework for reviewing heterogeneous bodies of evidence, especially in emerging or interdisciplinary fields (Tricco et al., 2018). A scoping review design was selected as it allows for the systematic mapping of key concepts, types of evidence and research gaps in areas where the evidence base is still evolving, such as the use of AI in women's career development. Given that empirical evaluations of AI-enabled career interventions with an explicit focus on women remain emergent, a small and heterogeneous evidence base was anticipated, and a scoping review approach was therefore appropriate for mapping what currently exists. To ensure methodological rigour and replicability, this review followed a preregistered protocol, which established clear eligibility criteria, the systematic search strategy, rigorous screening procedures and a transparent data synthesis plan. It is publicly accessible via the Open Science Framework (OSF): https://osf.io/a8qf7/?view_only=d39e5ea5225440db8e6df4e44a9b290a.

Eligibility criteria

Inclusion and exclusion criteria were defined to ensure the relevance, focus and empirical grounding of the included literature. Eligible studies cumulatively met the following criteria:

- Investigated interventions and/or technologies related to career development;
- Incorporated AI tools or techniques, including ML, GenAI or NLP;
- Focused explicitly on women and girls or examined gender-relevant challenges in career contexts;
- Employed empirical methods (qualitative, quantitative or mixed);
- Were published in English.

Studies were excluded if they:

- Did not involve AI-based technologies (e.g. only discussed digital platforms without AI components);
- Focused on career guidance without a developmental or supportive intervention component;
- Were non-empirical (e.g. theoretical articles, opinion pieces or editorials);
- Did not include a gender-specific analysis or focus on women.

Further detail on the empirical inclusion criteria and screening procedures is provided in the Appendix.

Information sources and search strategy

A systematic literature search was conducted between November 2024 and March 2025, across seven major databases, to ensure comprehensive coverage of interdisciplinary evidence: PubMed, Scopus, Web of Science, APA PsyInfo, APA PsycArticles, Psychology and Behavioral Sciences Collection and Google Scholar. The inclusion of both STEM-oriented and social science databases reflects the interdisciplinary nature of the research question, spanning educational technology, gender studies, psychology and labour market policy.

Backward and forward snowballing techniques were applied to the reference lists of included studies to identify additional relevant publications. All sources, including those identified via snowballing, were assessed using the same screening protocol and eligibility criteria.

The search strategy was structured around three core concept clusters:

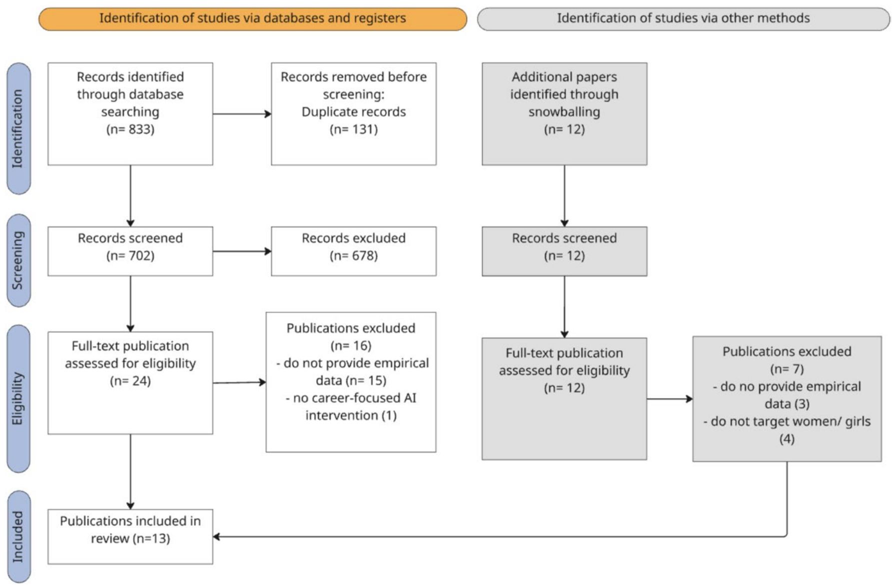

Fig. 1 PRISMA flow diagram

1. AI technologies: “artificial intelligence”, “machine learning”, “natural language processing”, “generative AI”, “chatbots”, “algorithmic tools”.
2. Career development: “career guidance”, “career coaching”, “professional mentoring”, “career advancement”, “skill development”.
3. Gender focus: “women’s career development”, “gender equity”, “girls in STEM”, “women in tech”, “gender bias”.

Boolean operators (AND/OR) and appropriate truncation symbols were applied. Searches were limited to the period 2010 to March 2025 to capture developments in AI technologies relevant to career development within a contemporary context.

Selection of sources of evidence

The screening process followed a two-step approach using Rayyan (rayyan.ai) to facilitate blinded, independent screening by two reviewers. Records were identified through two routes: (1) database searching and (2) snowballing. Following deduplication (n = 131), titles and abstracts of 702 unique records were screened for relevance, and 24 full-text reports were retrieved from the database search and assessed for eligibility against the predefined criteria. Snowballing identified an additional 12 records, of which five met the inclusion criteria. In total, 36 full-text reports were assessed (24 from databases + 12 from snowballing), and 13 empirical studies were included in the final synthesis. Discrepancies were resolved through discussion, with a third reviewer consulted where consensus could not be reached.

Data charting process

A structured data charting form was designed and piloted prior to full extraction to ensure consistency and completeness. For each included study, the following information was extracted:

- Author(s) and publication year;
- Country or region of study;
- Target population and sample characteristics;
- Study objectives and methodological approach;
- Type of AI technology or application deployed;
- Career-related outcomes assessed;
- Theoretical frameworks or conceptual models applied;
- Reported ethical, practical or technological challenges.

Two reviewers independently charted the data, and 15% of entries were cross-checked by a third reviewer to ensure inter-rater reliability and internal validity.

Data analysis and synthesis

The extracted data were synthesised using an inductive thematic analysis approach, guided by the work of Braun and Clarke (2023) and Saldaña (2021). This method is well-suited for scoping reviews aiming to generate conceptual clarity across heterogeneous studies. The analytic process followed six iterative steps:

1. Familiarisation with included studies;
2. Initial inductive coding of relevant features and themes;
3. Generation of candidate thematic categories;
4. Review and refinement of themes;
5. Mapping of studies to thematic domains;
6. Final synthesis aligned with the review's research objectives.

Ethical considerations

This study did not involve primary data collection and only analysed publicly available material. As such, it did not require ethical approval. Nonetheless, ethical reflexivity was maintained throughout the process, particularly in relation to

Table 1 Summary of included studies

Author(s)	Year	Country	Study type	Population	AI type	Theoretical framework	Career outcome(s)	Key findings
Alnuaimi & Tabbara	2023	UAE	Quantitative, predictive modelling	Employment data (36,897 instances)	Supervised ML (decision trees)	None reported	Career sustainability, attrition risk	Forecasted sustainable career paths; informed gender equity policy.
Alvarez et al.	2022	USA	Mixed methods	24 high school students (10 female, 14 male)	AI/ML curriculum with NLP APIs	Conceptual orientation (empirical inclusion studies)	AI literacy, computing career interest	Increased engagement and confidence in computing among participants.
Avery et al.	2023	USA	Field experiment	1295 applicants; 187 hiring evaluators	AI screening automation	Conceptual orientation (behavioural economics)	Recruitment equity, application completion	AI transparency improved application rates and reduced bias.
Elmorsy et al.	2024	Saudi Arabia	Quasi-experimental (pre–post)	45 female teachers	ChatGPT-based writing intervention	Conceptual orientation (GenAI in education)	Writing fluency, confidence	Improved writing skills and confidence via ChatGPT training.
Göritz et al.	2022	Germany	Pilot evaluation	Text evaluators	NLP for gender bias detection	Conceptual orientation (gender bias in education)	Bias detection in texts	AI matched human judgement in detecting gender bias.
Heath et al.	2019	USA	Quantitative, retrospective cohort	7326 evaluations for 521 faculty	NLP, text mining	Conceptual orientation (gendered language analysis)	Gender bias in evaluations	AI revealed persistent gendered descriptors in academic evaluations.
Lambrecht & Tucker	2018	Global	Field experiment	Digital advertisement platform users	ML-based advertisement delivery algorithm	Conceptual orientation (economic/legal theories)	Exposure to STEM careers	Algorithm prioritised men owing to cost optimisation.

Table 1 (continued)

Author(s)	Year	Country	Study type	Population	AI type	Theoretical framework	Career outcome(s)	Key findings
Meharunisa et al.	2024	Saudi Arabia	Quantitative (SEM)	180 faculty women	AI managerial systems (ML/NLP)	Empowerment theory; work–life balance theory	Empowerment, work–life balance	AI infrastructure was linked to better empowerment outcomes.
Vij et al.	2023	India	Quantitative, predictive modelling	HR data from women faculty	ML (logistic regression, decision trees)	Conceptual orientation (HR analytics, attrition)	Retention predictors	Work–life balance and advancement was linked to attrition.
Ramadan et al.	2024	Middle East	Quantitative, model development	962 women's résumés	NLP and ML; KNN classifier	Conceptual orientation (policy and inclusion reports)	Returnship alignment	Model aligned résumés to returnship jobs with 96.89% accuracy.
Sarraf et al.	2021	USA	Quantitative, retrospective	171 residency applicants	NLP and sentiment/emotion analysis	Conceptual orientation (bias frameworks)	Equity in medical education	LoRs showed gender bias; AI revealed emotional disparities.
Volpe & Simmons	2024	USA	Qualitative, narrative inquiry	Seven early career women engineers	GenAI (image-based)	Workforce sustainability model (Gambatese et al., 2019)	Representation, identity in engineering	AI visuals reinforced male-dominated imagery; alternatives were more inclusive.

Table 1 (continued)

Author(s)	Year	Country	Study type	Population	AI type	Theoretical framework	Career outcome(s)	Key findings
Wang et al.	2021	USA	Field experiment	308 general users (study 1) 296 general users (study 2)	Simulated AI career recommender (biased versus de-biased algorithms)	Conceptual orientation (HCI and fairness research)	Recommendation acceptance, perceived fit, trust	Users preferred gender-stereotypical recommendations, even when less accurate; human bias undermined algorithmic fairness.

how AI technologies may reproduce or challenge gendered power structures in professional contexts.

PRISMA flow diagram

The study selection process is summarised in Figure 1 (PRISMA flow diagram). Records were identified via database searching (n = 833) and snowballing (n = 12). After screening and eligibility assessment, 13 studies met the inclusion criteria and were included in the synthesis.

Results

Overview of included studies

In total, 13 empirical studies published between 2018 and 2025 were included. Most were conducted in the USA (n = 6) and the Middle East (n = 5), with one study each from India and Germany. This distribution indicates a marked geographical concentration and a limited European evidence base, despite Europe's active policy engagement with both gender equity and AI governance. Table 1 summarises study characteristics and key findings.

Methodological characteristics

Most included studies adopted quantitative designs (n = 9), including predictive modelling, structural equation modelling and survey-based analyses. The remaining evidence comprised one qualitative narrative inquiry, one mixed-methods study, one quasi-experimental intervention and one design validation. Target populations varied by career stage and context, including secondary and university students, early career professionals in male-dominated fields, women in academic settings, job applicants and workforce returners and general users interacting with career recommender systems.

AI technologies and outcomes assessed

Studies employed a range of AI approaches, most commonly NLP and ML, often applied to large institutional or platform datasets. A smaller set of studies used GenAI, typically for coaching, simulation, writing support or visual representation tasks. Outcomes assessed clustered around: (1) bias detection and representational equity (e.g. gendered language in evaluation materials, advertisement delivery disparities or stereotyping), (2) skills and confidence development (e.g. writing fluency, AI literacy and self-efficacy) and (3) career pathways and sustainability (e.g. job matching, returnship alignment, attrition risk and retention).

Theoretical framing

Formal theory use was limited. Two studies explicitly anchored their design or interpretation in established frameworks (empowerment theory; workforce sustainability model), whereas most studies relied on broad conceptual orientations (e.g. fairness/bias frameworks, behavioural economics and human–computer interaction) rather than career-development theory. Overall, the evidence base shows stronger emphasis on technical function and measurement than on theory-driven explanation of how AI influences career development processes.

Ethical considerations

Ethical issues were reported inconsistently across studies and were most prominent in hiring, screening and sentiment-analysis applications. Recurring concerns included algorithmic bias and unintended discrimination, limited transparency and user control over AI outputs, cultural limitations in training data (particularly for GenAI systems) and limited stakeholder engagement, especially involving women from marginalised groups.

Table 2 Thematic categorisation

Study	Thematic focus
Avery et al. (2023)	AI for bias mitigation and representation; AI for career pathways and retention
Göritz et al. (2022)	AI for bias mitigation and representation
Heath et al. (2019)	AI for bias mitigation and representation
Lambrecht and Tucker (2018)	AI for bias mitigation and representation
Sarraf et al. (2021)	AI for bias mitigation and representation
Volpe and Simmons (2024)	AI for bias mitigation and representation
Wang et al (2021)	AI for bias mitigation and representation
Alvarez et al. (2022)	AI for skills development and empowerment
Elmorsy et al. (2024)	AI for skills development and empowerment
Meharunisa et al. (2024)	AI for skills development and empowerment; AI for career pathways and retention
Alnuaimi and Tabbara (2023)	AI for career pathways and retention
Ramadan et al. (2024)	AI for career pathways and retention
Vij et al. (2023)	AI for career pathways and retention

Summary table

A comprehensive summary of the study characteristics, including year, location, AI type, population, methodology, theoretical framework, outcomes and key findings, is provided in Table 1. This table offers a foundation for the thematic synthesis that follows, wherein studies are grouped according to the primary function of AI in supporting women's career development.

Thematic content analysis

Inductive thematic analysis identified three overarching ways in which AI was being applied in relation to women's career development (Table 2). These domains were derived from patterns in the included studies and reflect both where AI intervened and the outcomes targeted. Consistent with the Systems Theory Framework (STF), they capture AI operating at different levels of influence: (1) institutional and societal career systems (e.g. recruitment, evaluation and representation), (2) individual learning and agency within supportive contexts and (3) organisational decision infrastructures shaping sustainability and progression over time. They also align with Social Cognitive Career Theory (SCCT) by distinguishing applications that primarily influence perceived supports and barriers and outcome expectations (theme 1), self-efficacy and goal-relevant skills (theme 2) and choice actions and sustaining conditions (theme 3). Several studies contributed to more than one domain, reflecting the interdependence of bias, capability development and sustained career participation.

Theme 1: AI for bias mitigation and representation (*n* = 7)

This theme included studies using AI to detect gendered language and evaluative bias in professional texts, examine disparities in recruitment and advertising systems, assess representational bias in GenAI outputs and explore user responses to fairness-aware recommendations (Avery et al., 2023; Göritz et al., 2022; Heath et al., 2019; Lambrecht & Tucker, 2018; Sarraf et al., 2021; Volpe & Simmons, 2024; Wang et al., 2021). Across studies, AI was used both as a diagnostic tool to expose gender bias and, in several cases, as an intervention component shaping recruitment and career decisions. NLP applications were frequently deployed to identify gendered language and evaluative patterns in high-stakes professional texts (e.g. letters of recommendation and faculty evaluations), indicating that automated approaches can support scalable monitoring of institutional bias. In recruitment and advertising contexts, evidence highlighted AI's dual potential: increased transparency and regulated deployment were associated with improved perceptions of fairness and reduced disparities, while optimisation-driven systems (e.g. cost-efficiency in digital advertising) risked reproducing structural inequalities. GenAI evidence further suggested that representational bias can be embedded in outputs (e.g. male-dominant imagery of engineers) unless prompts, datasets and design choices are deliberately equity-oriented. Finally, user-facing recommender systems illustrated that technical de-biasing may be undermined by users' stereotype-congruent preferences, indicating that fairness-aware systems must consider how end-users interpret and adopt recommendations. Overall, the evidence positions AI as a promising mechanism for detecting and auditing gender bias, while also showing that without intentional governance and design, AI tools may reproduce or legitimise existing inequities. These studies show AI operating within career systems that structure opportunity and representation, largely through shaping perceived barriers/supports and what outcomes appear realistic or rewarding.

Theme 2: AI for skill development and empowerment (*n*=3)

Studies in this theme evaluated AI as a developmental support for women's skills, confidence and agency, primarily through structured learning or training interventions (Alvarez et al., 2022; Elmorsy et al., 2024; Meharunisa et al., 2024). Interventions included AI-supported writing development and curricula designed to increase engagement with computing and AI-related careers among female students. Reported outcomes were mainly proximal, such as improvements in writing performance, confidence and perceived competence. One study also linked AI-enabled managerial infrastructure with empowerment and work–life balance, indicating that AI may support empowerment not only through individual capability-building but also through organisational systems that shape workload, feedback and flexibility. Overall, these interventions primarily targeted individual agency by strengthening self-efficacy, confidence and goal-relevant skills within supportive pedagogical or organisational contexts, although evidence remains largely short-term.

Theme 3: AI for career pathways and retention (*n* = 5)

This theme comprised predictive and assistive applications intended to support career sustainability, job matching and retention-related outcomes, including attrition-risk modelling and the alignment of women's profiles with roles or returnship opportunities (Alnuaimi & Tabbara, 2023; Avery et al., 2023; Meharunisa et al., 2024; Ramadan et al., 2024; Vij et al., 2023). Predictive modelling approaches identified variables associated with women's workforce participation and potential attrition, offering signals that could inform organisational planning and policy. Matching-focused applications positioned AI as a tool to improve fit between opportunities and women's profiles and constraints, including career re-entry scenarios. These applications sit most clearly in organisational decision infrastructures, influencing sustainability and progression by shaping opportunity alignment, constraints and conditions for persistence. Across studies, however, evaluation tended to focus on model performance or short-term outcomes, with limited evidence on downstream impacts such as sustained retention, progression or wellbeing. Overall, AI shows potential to support career sustainability through prediction and matching, but robust evaluation of longer-term outcomes remains scarce.

Cross-theme comparison

Across themes, bias mitigation and representation dominated the evidence base, likely because text and platform-based datasets (e.g. evaluations, advertisements and recommendation letters) are readily available and amenable to automated auditing. Skills and empowerment interventions were less common, consistent with the greater resource demands of designing, implementing and evaluating developmental programmes. Studies on pathways and retention appear to be emerging alongside increased organisational adoption of Human Resources (HR) analytics and decision-support systems, but the evidence base remains largely predictive or pilot-level.

Discussion

This scoping review indicates that empirical work on AI supporting women's career development is coalescing around three functions – bias/representation, skills/empowerment and pathways/retention – although these functions are unevenly developed. Consistent with a multi-level view of career development, these functions map onto different points of intervention: system-facing applications that structure opportunity and representation, individual-facing applications that support agency and capability and organisational infrastructures that shape sustainability over time (McMahon & Patton, 2022; Patton & McMahon, 2006). They also align with core career processes emphasised in social cognitive accounts, in which perceived supports and barriers, self-efficacy, outcome expectations and goals influence career behaviour and persistence (Brown & Lent, 2023).

Socio-technical accounts emphasise that AI is shaped by social and organisational contexts in both its design and deployment rather than operating as a neutral tool (Avis, 2018). This is reflected in the included studies, where AI is positioned less as a stand-alone intervention and more as part of organisational and platform processes that structure career-related opportunities. This emphasis on digitally mediated, data-informed career support aligns with wider discussions on the transformation of career interventions in the digital age (Lent, 2025) and with evidence that AI-enabled guidance is increasingly framed as data-informed decision-support systems (Manganello et al., 2025). Together, these findings extend prior conceptual accounts by showing that the women-focused empirical literature mapped in this review concentrates on system-facing applications, while developmental and longitudinal career outcomes remain comparatively under-evaluated.

Consistent with the analytic aims, the evidence is weighted towards audit-friendly, system-facing studies, and this imbalance is partly methodological. Bias/representation studies dominate not simply because bias is a salient problem but also because bias in text and platforms is comparatively audit-friendly: institutional datasets such as evaluations, recommendation letters and advertising logs are already digitised, high volume and amenable to NLP/ML. This enables inequity to be detected and quantified without long intervention cycles or follow-up, whereas sustained outcomes require longitudinal tracking. Skills/empowerment interventions, by contrast, require programme design, sustained engagement and outcome measurement beyond immediate performance gains, making them harder to execute and publish within typical organisational constraints. However, although most evaluations of these interventions are short term, approaches that build women's self-efficacy and support goal-directed career behaviours remain promising, given strong evidence linking these variables to agency and adaptive behaviour change (Choi et al., 2012; Lent et al., 2017). Pathways/retention studies sit in between, often framing support as prediction or matching rather than as demonstrable improvement in women's lived career experiences or progression over time.

The synthesis surfaces a recurring tension: even when AI is engineered towards fairness, equity is not guaranteed in practice. Users may favour stereotype-congruent recommendations even when fairness-aware alternatives are available, indicating that equitable guidance depends on how outputs are interpreted and acted upon, not only on algorithmic properties (Wang et al., 2021). Likewise, optimisation objectives can produce gender-skewed exposure without explicit discriminatory intent, because disparity can arise through ostensibly neutral performance criteria such as cost-efficiency (Lambrecht & Tucker, 2018). By bringing these strands together, this review highlights that fairness-aware design is insufficient unless it is matched by governance at the point of deployment and use. Accordingly, these findings make governance – objectives, constraints, monitoring and contestability – central to equity outcomes and support treating the socio-technical system (model, interface, organisational incentives and users' interpretation and action) as the appropriate analytic focus for explaining why technical de-biasing alone may not translate into equitable career trajectories.

These dynamics have direct implications for how AI should be evaluated and governed in career development contexts. Effectiveness should be judged not only by predictive performance or user satisfaction but also by whether systems expand women's viable opportunities and support agency, rather than channelling users into norm-congruent roles. Transparency must be functional rather than cosmetic: explainability is only valuable if it supports contestability and user agency, i.e. the ability to question, override and contextualise recommendations. Stakeholder engagement is not simply an ethical add-on; it is a design requirement for relevance and legitimacy, particularly when systems may encode dominant norms into what counts as fit, success or leadership. These points align with scholarship that conceptualises AI as a site of power and governance, where equity depends on whose values are encoded in system design, deployment and accountability arrangements (Syeda, 2023; Toupin, 2023). Overall, these findings support a human-in-the-loop model: AI may scale access to information and feedback, but it cannot substitute for contextual judgement, value clarification and fairness oversight in career decision-making.

Limitations

This review is limited by the small and heterogeneous evidence base (n = 13). Although this is consistent with an emerging field, the limited number of studies constrains inference beyond mapping the current landscape and reduces confidence in transferability across settings. Substantial variation in interventions, methods and outcome measures also limited cross-study comparability. In addition, the evidence is geographically uneven, with minimal representation from Europe, which restricts transferability to European vocational guidance systems and labour-market contexts.

A further limitation concerns the limited use of structured conceptual and theoretical frameworks to inform the design, interpretation and evaluation of AI interventions. Only a small minority of studies explicitly applied formal theory, while many drew on broad conceptual orientations without specifying mechanisms linking intervention features, context and career-development outcomes. This weak theoretical integration limits interpretive depth and reduces cumulative insight across studies.

Implications for practitioners

For practitioners working in schools, higher education, public employment services, community/lifelong guidance and organisational career development settings, the reviewed studies suggest that AI is most appropriately positioned as decision support within guidance processes, where outputs are interpreted in context and can be scrutinised for bias. Practically, AI may help widen occupational and learning options, support skills rehearsal (e.g. CVs, applications, interview preparation) and surface potentially biased language or recommendations; however, these benefits depend on sufficient AI literacy among both practitioners and guidance recipients to interrogate outputs rather than accept them as authoritative. This includes understanding that AI suggestions can reflect stereotypes, optimise for convenience rather than equity and vary across time and settings; accordingly, AI use should be accompanied by explicit reflective prompts (e.g. 'what assumptions are embedded here?', 'what options are missing?' and 'whose definition of fit is being applied?') and deliberate generation of non-stereotypical alternatives. This also implies a role for guidance services in setting clear guidance on which AI tools can be used, providing staff training on responsible use and establishing a simple process for flagging and reviewing biased or unsafe outputs.

Where AI is used for drafting or coaching, outcomes are more likely to be constructive when use is scaffolded (clear goals, iterative feedback and reflection) so that individuals retain authorship and self-efficacy rather than outsourcing judgement. Importantly, responsible use is not a one-off check: practitioners and services should periodically review the kinds of outputs being produced (including any systematic differences by gender or career pathway), because tools can change with updates, local configurations or shifts in how people rely on them, with potential behavioural effects that accumulate over time. Basic safeguards remain essential, including avoiding the entry of identifiable personal data into public tools, being transparent about when and how AI is used and supporting guidance recipients to challenge, contextualise and – where needed – disregard AI outputs in favour of informed, values-based decisions.

Implications for policymakers

Policymakers should treat AI-enabled career guidance as a high-stakes socio-technical practice and set minimum standards for transparency, accountability and equity. Priorities include requirements for monitoring disparate impacts over time, ensuring contestability (clear routes to challenge and remedy harmful outputs) and protecting privacy in guidance contexts. Given that systems and outputs may change through updates or drift, policy should also require periodic re-evaluation and reporting rather than one-off approval at procurement or launch. Finally, policy should support AI literacy at the population level, particularly for women and girls facing compounded barriers, to ensure that AI tools expand opportunity rather than deepen digital inequalities.

Implications for developers

Developers should embed equity and accountability into the full life cycle of AI career tools through explicit design principles. These include: (1) bias-by-design, with auditing across training data, model outputs and interface defaults (including ranking logic and fit scores); (2) meaningful transparency, providing explanations that users and practitioners can interrogate rather than opaque recommendations; (3) user agency and control, enabling users to adjust constraints, explore alternatives and override or contest outputs; (4) anti-stereotype design, avoiding default pathways that narrow options and ensuring the system actively supports exploration and counter-stereotypical recommendations; and (5) continuous monitoring, with evaluation for drift, performance changes and disparate impacts over time. These principles should be strengthened through participatory co-design and testing with diverse women, including marginalised groups, to ensure that definitions of fit, success and quality are not implicitly aligned with dominant norms.

Future research directions

Future research should strengthen the evidence base through designs that enable causal and contextual inference about how AI shapes women's career development. Priorities include longitudinal and mixed-methods studies that track sustained effects on career trajectories, self-efficacy, identity and indicators of psychological and subjective well-being, including job/work satisfaction and work-related well-being (i.e. measurable improvements in the relationship with work), and intersectional approaches that examine differential impacts by ethnicity, disability, migration status, socio-economic position and geography. To support cumulative knowledge, studies should be more explicitly theory-informed, specifying mechanisms that link AI features and deployment conditions to career-development constructs by integrating vocational psychology, gender theory and socio-technical perspectives. Addressing the current geographical skew will also require cross-national, multi-site research across diverse guidance systems and labour-market contexts.

As GenAI becomes more prevalent in mentoring, feedback and decision support, research should examine not only performance and user satisfaction but also agency, stereotype reinforcement and behavioural effects that may accumulate over time. Finally, greater attention is needed to governance and ethics, including evaluation frameworks that incorporate transparency, contestability, privacy and ongoing monitoring for drift and disparate outcomes in real-world educational and vocational guidance environments.

Conclusions

This scoping review mapped the emerging empirical literature on AI-enabled applications supporting women's career development and organised the evidence into three functional domains: bias mitigation and representation, skills development and empowerment and career pathways and retention. Across studies, AI is currently more strongly evidenced as a tool for auditing and shaping career-related systems. By contrast, there is limited empirical support for AI-enabled interventions demonstrating sustained career development outcomes. Overall, the review indicates that equity outcomes are likely to be shaped not only by technical performance, but by design, governance and context of use within guidance and organisational settings.

Appendix

Screening criteria and review procedures

Screening procedure

A two-stage screening process was conducted using Rayyan (rayyan.ai) to ensure rigour and reviewer independence:

- Stage 1 – title and abstract screening: two independent reviewers assessed 702 deduplicated records for initial relevance on the basis of predefined inclusion criteria.
- Stage 2 – full-text screening: 24 full-text articles were evaluated in detail. Discrepancies at either stage were resolved through discussion; a third reviewer was involved where necessary.

Inclusion criteria

To qualify for inclusion, studies had to present original data collection and analysis. Eligible methodologies included qualitative (e.g. interviews, case studies), quantitative (e.g. surveys, experiments) and mixed methods. Excluded were theoretical or conceptual papers, editorials and literature reviews without original data.

Snowballing and additional sources

Backward and forward snowballing techniques were applied to the reference lists and citation networks of included studies. Additional sources retrieved from broad-based databases such as Google Scholar occasionally included non-traditional formats (e.g. conference papers); all were assessed using the same screening protocol and eligibility criteria as peer-reviewed articles.

Exclusion criteria

Studies were excluded if they were theoretical or conceptual papers, editorials or literature reviews without original data. Full-text articles were excluded if they did not report original empirical data, did not involve AI-based technologies, lacked a gender-specific focus or did not include a developmental or supportive component related to career guidance. These reasons applied equally to sources identified via database searches and snowballing. All exclusion decisions were guided by the predefined eligibility criteria and are summarised in the PRISMA flow diagram (Figure 1).

Author contributions Sara Portell-Fonolla: conceptualisation; methodology; protocol development; literature search; data curation; formal analysis; writing: original draft; project administration. Yasmina El Fassi: screening and article selection; data extraction; writing: review and editing. Augusta D. Gaspar: conceptualisation; project supervision; writing: review and editing. Luis Correia: project supervision. Joana Carneiro Pinto: conceptualisation; validation (third reviewer); writing: review and editing; project supervision. All authors reviewed and approved the final manuscript.

Funding Open access funding provided by FCT|FCCN (b-on).

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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