International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://theaspd.com/index.php

An AI-Powered Framework for Skill Assessment and Personalized Career Pathway Recommendation in STEM and Coding Courses for High School Students: A Systematic Literature Review

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Abstract
Background: *Artificial Intelligence (AI) is increasingly applied in secondary Science, Technology, Engineering, and Mathematics (STEM) and coding education to enhance skill assessment and guide career decision-making. By analysing learner data, AI frameworks can identify strengths, address skill gaps, and recommend personalised academic and vocational pathways. However, integration into unified, pedagogically aligned systems remains limited, and research activity is unevenly distributed across regions.*
Objective: *This review synthesises peer-reviewed literature on AI-powered frameworks that combine skill assessment with career pathway recommendation in secondary-level STEM and coding education, with a focus on methodological trends, geographic distribution, and pedagogical implications.*
Methodology: *A systematic search, following PRISMA 2020 guidelines, was conducted across Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and ERIC for publications from 2010 to 2025. Studies were eligible if they were peer-reviewed, published in English, and applied AI techniques, such as machine learning, deep learning, or other algorithmic methods, for skill assessment or career recommendation in secondary STEM contexts.*
Results: *Machine Learning was the dominant AI technique (50.0%), while hybrid recommender systems integrating content-based and collaborative filtering were the most prevalent career guidance approach (40.0%). Research output was concentrated in the Middle East (25.0%) and Asia-Pacific (25.0%), followed by Europe (15.0%), with Latin America and North America each contributing 10.0% and Africa 5.0%. Explainable AI was present in 10.0% of studies, indicating gradual but limited adoption.*
Conclusion: *AI demonstrates strong potential to enhance differentiated instruction, early skill-gap detection, and personalised career guidance in secondary STEM education. To maximise impact, future research should address geographic imbalances, embed pedagogical theory into system design, and advance interpretable multi-modal hybrid models adaptable to diverse educational contexts.*
Keywords: *Artificial Intelligence in Education, STEM Skill Assessment, Career Pathway Recommendation, Hybrid Recommender Systems, Explainable AI in Schools*

1. INTRODUCTION

The rapid evolution of Artificial Intelligence (AI) is transforming education by enabling unprecedented levels of personalisation, efficiency, and scalability [1]. In the context of STEM (Science, Technology, Engineering, and Mathematics) education, AI-powered systems are increasingly deployed to monitor learning progress, assess competencies, and deliver tailored feedback [2]. For secondary school students, particularly those engaged in coding and computational thinking, AI offers the potential to identify learning needs early, support informed academic choices, and align skill development with future career trajectories.

Global initiatives, such as UNESCO's Education 2030 Agenda and national STEM reform programmes, emphasise preparing students for technology-driven economies [3]. Within this framework, AI-driven

skill assessment tools can process diverse datasets, from code submissions and project artefacts to behavioural learning patterns, providing granular evaluations of student competencies. In parallel, AI-based career pathway recommendation systems can map these competencies to relevant academic or vocational opportunities, assisting learners at critical transition points in their education [4]. In coding education, where problem-solving, logical reasoning, and code quality are central, AI systems can evaluate not only correctness but also efficiency, structure, and style, enhancing both technical and analytical skills. Despite increasing integration of AI in education, its application in secondary-level STEM and coding contexts for combined skill assessment and career guidance remains fragmented [5]. Many existing systems focus exclusively on either evaluating technical skills or recommending career options, without integrating both into a coherent, adaptive framework. Development and deployment are also geographically uneven, with the Middle East and Asia-Pacific accounting for the largest research output, while Latin America and Africa remain significantly underrepresented [6].
A further limitation is the technical–pedagogical gap: although many AI models demonstrate high predictive accuracy for skills or career suitability, they are not consistently designed for pedagogical alignment or explainability [7]. This reduces trust and uptake among educators, students, and parents, particularly where AI recommendations may influence long-term academic and career decisions.
Most AI-in-education reviews focus on learning analytics, adaptive learning, or recommender systems, with little attention to AI frameworks that combine skill assessment and personalised career pathways for secondary STEM and coding [8]. Research skews toward higher education, lacks cross-regional validation, uses explainable AI in only 10% of cases, and underutilises hybrid recommenders, highlighting the need for a targeted, evidence-based synthesis to guide future development and policy.
This study fills these gaps through a systematic literature review (SLR) of peer-reviewed research published between 2010 and 2025 across Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and ERIC. Conducted by PRISMA 2020 guidelines, the review synthesises evidence on AI techniques applied to skill assessment and career pathway recommendations in secondary STEM and coding education; the types of career recommendation approaches adopted, including content-based, collaborative filtering, hybrid, and rule-based methods; the dataset sources, evaluation metrics, and performance outcomes reported; and the practical challenges, ethical considerations, and geographic distribution of the research.

This review maps AI-powered frameworks integrating skill assessment and career guidance in secondary STEM and coding education, highlighting dominant methodological trends, including Machine Learning (50%), hybrid recommendation systems (40%), and limited explainable AI (10%). It reveals regional disparities, with the Middle East and Asia-Pacific leading output, Europe showing methodological diversity, and Latin America and Africa underrepresented. Aligned with educational theory, it underscores the need for AI systems that are both technically robust and pedagogically relevant, offering policy guidance on equitable integration through infrastructure, capacity-building, ethics, and governance [9].

The structure of the review begins with an exploration of the evolution of AI in STEM education, highlighting its applications in skill assessment and career recommendation while critically evaluating existing studies. This is followed by a PRISMA-compliant methodology section detailing the search strategy, inclusion and exclusion criteria, and analytical procedures. The results are then presented through descriptive statistics, thematic synthesis, and visual summaries. The discussion section interprets the findings, compares them with prior literature, and addresses limitations, leading to the conclusion, which summarizes key takeaways and offers recommendations for future research.

2. LITERATURE REVIEW

2.1 Overview of AI in STEM Education

Artificial Intelligence (AI) has become a transformative force in STEM education, offering capabilities that extend well beyond automation. In secondary education, AI systems can process diverse and large-scale datasets, detect learning patterns, predict academic trajectories, and provide real-time, adaptive feedback [10]. These capabilities are particularly valuable in STEM disciplines, where mastery often requires iterative assessment, timely intervention, and personalised learning pathways. Recent research demonstrates AI's potential to enhance instructional efficiency, support competency-based learning, and facilitate student progression into advanced STEM studies [11].

2.2 AI for Skill Assessment in Coding and STEM

AI-powered skill assessment in coding and STEM contexts most frequently employs Machine Learning (ML) techniques, including decision trees, random forests, support vector machines, and neural networks, to assess coding outputs, analyse problem-solving behaviour, and forecast learning outcomes [12]. Deep Learning (DL) methods, though less common (5.0% of reviewed studies), offer advantages in handling unstructured inputs such as program structure, visual representations, and log data from problem-solving activities. Other approaches include Data Mining, Case-Based Reasoning, and AutoML, applied to optimise assessment accuracy and scalability.
Explainable AI is emerging in this domain, allowing educators and students to understand the reasoning behind predictions or evaluations, though current adoption is limited to 10.0% of studies. These technologies collectively enable granular identification of learner strengths, misconceptions, and development needs, supporting more targeted and timely pedagogical interventions [13].

2.3 AI for Career Pathway Recommendation

Career pathway recommendation systems in secondary STEM education aim to match learner competencies and interests with academic and career trajectories [14]. Hybrid recommendation systems integrating content-based filtering and collaborative filtering are the most prevalent approach (40.0% of studies), valued for their adaptability and ability to leverage diverse data sources [15]. Content-based filtering (25.0%) aligns learner profiles with career requirements, while Collaborative filtering (15.0%) uses patterns from peer pathways. Rule-based methods (20.0%) remain in use where transparency and domain expertise are paramount.
Some recent systems incorporate behavioural and contextual data, such as participation in extracurricular activities or engagement in digital learning environments, to generate richer learner profiles. The integration of Explainable AI remains limited but is recognised as a critical step toward ensuring that recommendations are transparent, interpretable, and ethically aligned.

2.4 Critical Analysis of Reviewed Studies

Machine Learning dominates as the foundational AI technique in this field (50.0%), reflecting its adaptability and proven track record in educational prediction and classification tasks. Hybrid recommendation systems show the greatest potential for personalisation, combining multiple algorithms to mitigate the limitations of single-strategy approaches. Regionally, the Middle East (25.0%) and Asia-Pacific (25.0%) lead research output, often driven by strategic government STEM initiatives, while European research (15.0%) tends to emphasise methodological innovation, such as network visualisation and multi-modal integration.
Latin America (10.0%) and Africa (5.0%) remain underrepresented, raising concerns about inclusivity and the generalisability of AI frameworks. Methodological limitations include reliance on small or institution-specific datasets, inconsistent reporting standards, and insufficient integration of pedagogical theory, which can limit the educational relevance of technically robust systems [16].

2.5 Summary of Reviewed Literature

The literature highlights AI's potential to improve the precision, personalisation, and scalability of skill assessment and career guidance in secondary STEM education. The field shows a marked shift toward hybrid architectures and the early adoption of explainable AI, indicating a maturation toward systems that are both technically advanced and more interpretable for end-users. However, significant work remains to address geographic imbalances, strengthen methodological transparency, and ensure that AI system design is grounded in pedagogical principles.

2.6 Thematic Synthesis

The review identifies three key themes: a shift toward hybrid AI frameworks that enhance adaptability and accuracy through diverse data integration; limited adoption of explainable AI despite growing recognition of its importance (10% of studies); and persistent geographic disparities, with research concentrated in the Middle East, Asia-Pacific, and Europe, underscoring the need for cross-regional validation and inclusive, culturally relevant design.

3. MATERIALS AND METHODS

3.1 Review Protocol

The systematic literature review was carried out by the PRISMA 2020 guidelines to ensure methodological rigor, transparency, and reproducibility. A structured review protocol was defined in advance, specifying the scope, research questions, search strategy, inclusion and exclusion criteria, and data analysis methods. The review aimed to systematically identify, evaluate, and synthesize studies on AI-powered frameworks for skill assessment and personalized career pathway recommendations in STEM and coding courses targeted at high school students. The research addressed four primary questions related to the AI techniques employed, the types of career recommendation methods used, the datasets and evaluation metrics applied, and the practical challenges and ethical concerns documented in the literature.

3.2 Search Strategy

A comprehensive literature search was conducted across Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and ERIC to ensure wide coverage of both education and AI research. The search covered studies published between 2010 and 2025 to capture the most recent technological and pedagogical advancements. A carefully structured Boolean search query combined AI-related terms with educational keywords and contextual constraints, for example: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing") AND ("skill assessment" OR "competency evaluation" OR "learning analytics") AND ("STEM" OR "coding" OR "programming") AND ("career recommendation" OR "career pathway" OR "career guidance") AND ("high school" OR "secondary school" OR "K-12"). All search results were exported into a reference manager for processing, and duplicate records were removed both automatically and manually to ensure accuracy.

3.3 Inclusion and Exclusion Criteria

The inclusion criteria specified that studies must have been peer-reviewed journal or conference papers, written in English, and explicitly applied AI, machine learning, or deep learning methods for skill assessment or career pathway recommendations in high school STEM or coding education. To be eligible, studies were required to present empirical results supported by evaluation metrics. Exclusion criteria ruled out works without AI integration, those focused solely on higher education or professional training, studies with insufficient methodological detail, and non-peer-reviewed outputs such as posters, editorials, or short abstracts. Duplicates and preprints without full peer review were also excluded to maintain the integrity of the evidence base.

3.4 Algorithmic Review Flow

The review process followed a structured sequence:
Step 1: Define research scope and questions.
Step 2: Identify keywords and Boolean search strings.
Step 3: Search five major databases (2010–2025).
Step 4: Export and deduplicate all retrieved records.
Step 5: Screen titles and abstracts against inclusion/exclusion criteria.
Step 6: Conduct full-text eligibility review.
Step 7: Extract data using a standardized template.
Step 8: Assess methodological quality with MMAT.
Step 9: Perform descriptive and thematic synthesis.
Step 10: Generate tables, figures, and summary visualizations.

3.5 Box Diagram Workflow

The workflow begins with defining the scope and research questions, followed by keyword identification, database searches, and duplicate removal. Studies are screened by title and abstract, assessed for full-text eligibility, and final inclusions undergo data extraction and quality appraisal (MMAT), concluding with descriptive and thematic synthesis, as shown in Figure 1.

International Journal of Environmental Sciences
ISSN: 2229-7359
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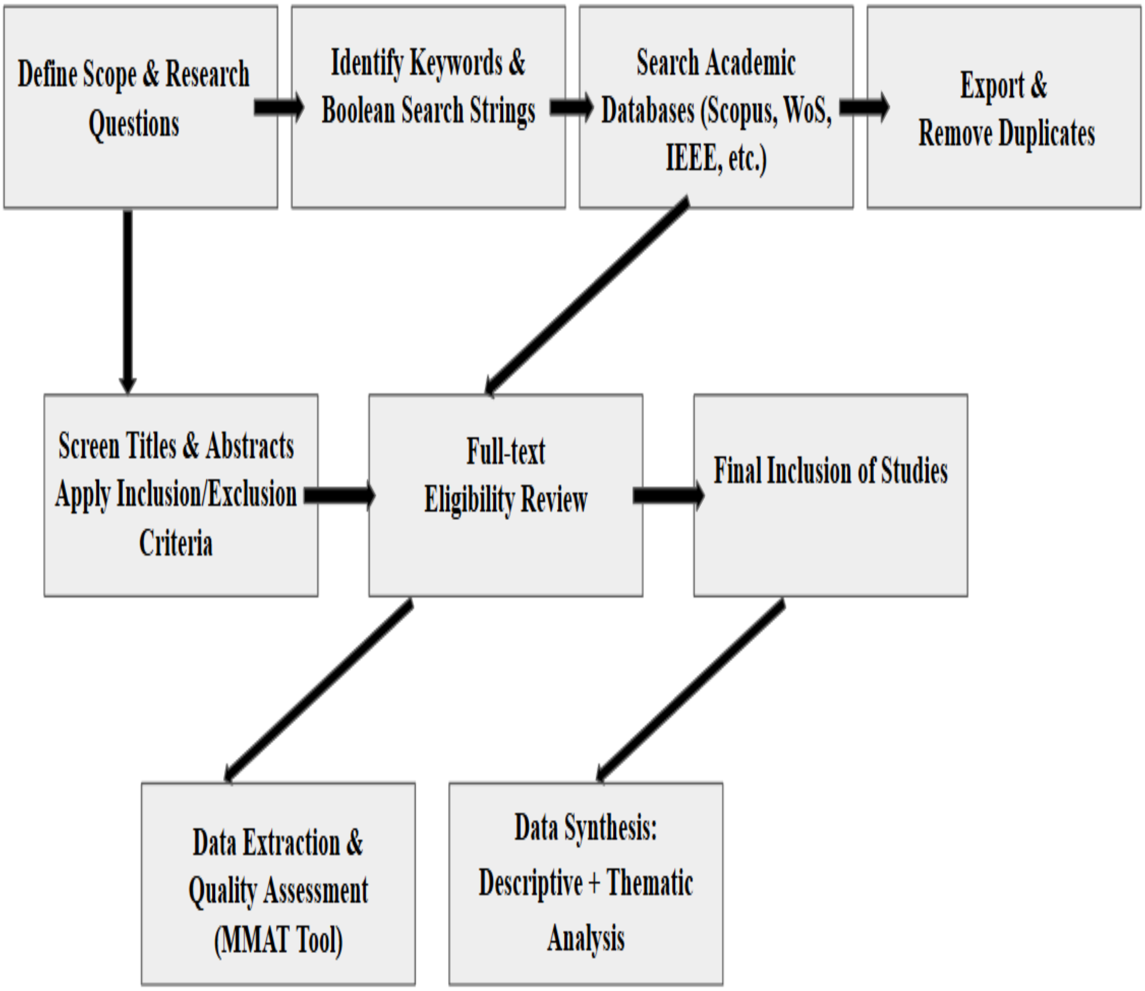

Figure 1. Systematic Literature Review Workflow

3.6 Dataset Description

The final review dataset consisted of 20 empirical studies meeting all eligibility criteria. Data variables included:

- Bibliographic details: authors, year, country/region.
- Educational domain: STEM sub-area, coding or computational thinking.
- Technical details: AI techniques/models, recommendation approaches.
- Dataset source type: institutional records, national databases, online logs, surveys.
- Evaluation metrics: accuracy, precision, recall, F1-score, user satisfaction, and explainability metrics.
- Contextual factors: ethical considerations, limitations, and pedagogical alignment.

Data were stored in a structured spreadsheet to facilitate statistical and thematic analysis.

3.7 Study Selection Process

The selection process followed the four PRISMA stages. During the identification stage, all records retrieved from database searches were compiled in a unified library. In the screening stage, titles and abstracts were reviewed to remove irrelevant or ineligible works. The eligibility stage involved a detailed full-text review to verify compliance with the inclusion criteria. Finally, the inclusion stage produced the final list of studies to be analyzed. Each stage of this process, including the number of records excluded and the reasons for exclusion, was documented in a PRISMA flow diagram, ensuring transparency and reproducibility of the study selection, as shown in Figure 2.

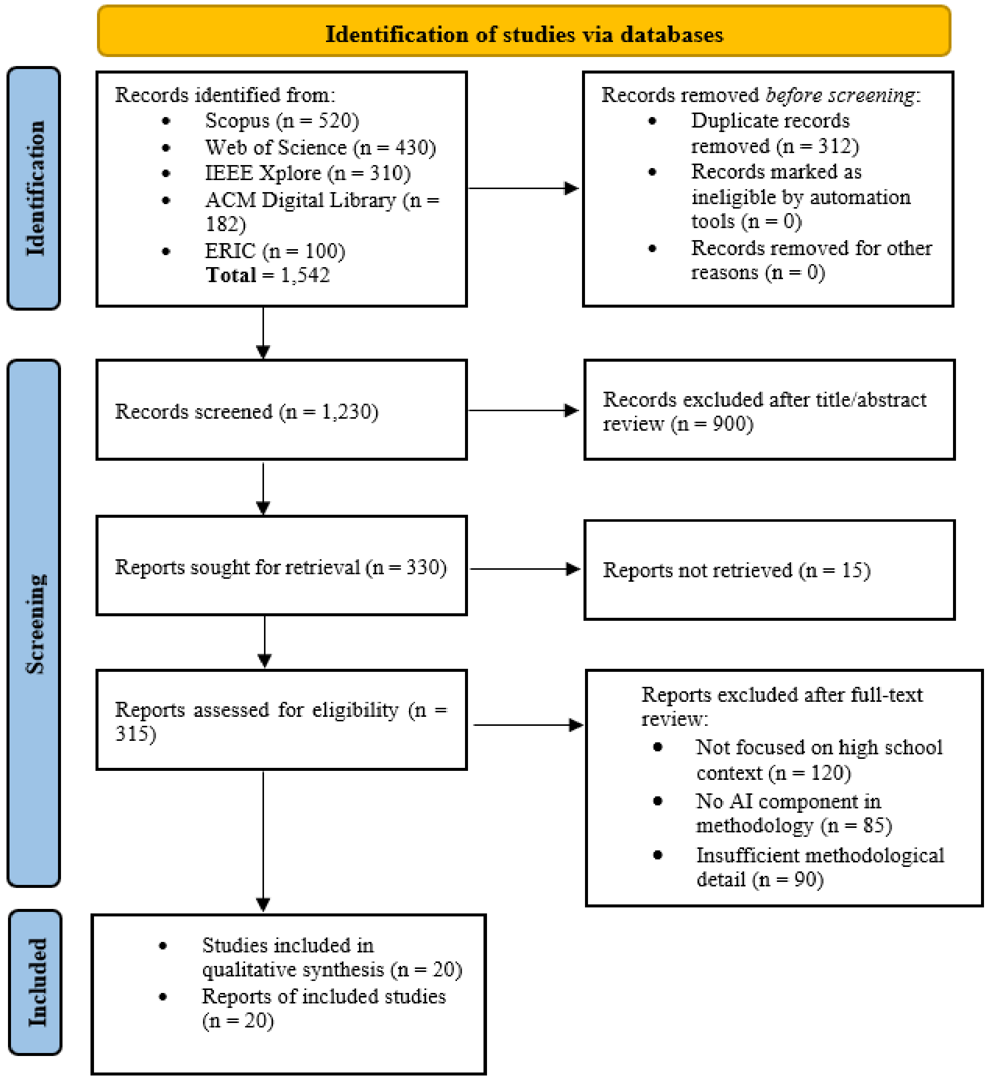

Figure 2. PRISMA 2020 flow diagram for AI-based skill assessment and career pathway recommendations in high school STEM and coding

3.8 Data Extraction

Data were extracted from the included studies using a standardized template to ensure completeness and consistency. Extracted information included authors, year of publication, country or region of study, the educational domain and target STEM area, the AI techniques and models employed, dataset characteristics (source, size, and type), evaluation metrics, performance outcomes, reported advantages and limitations, and any ethical or privacy considerations. Data extraction was conducted independently by multiple reviewers, and discrepancies were resolved through discussion to ensure accuracy.

3.9 Quality Assessment

The methodological quality of each included study was evaluated using the Mixed Methods Appraisal Tool (MMAT), which provided a structured framework for assessing diverse research designs. Criteria included the clarity of research objectives, the appropriateness of the AI technique for the stated goals, dataset adequacy and representativeness, the suitability of evaluation metrics, transparency in methodology, and depth of discussion regarding limitations and ethical aspects. Studies scoring 75% or higher were classified as high quality, those scoring between 50% and 74% as moderate quality, and those scoring below 50% as low quality. Differences in scoring were discussed and resolved among the reviewers until a consensus was reached.

3.10 Data Synthesis

Data synthesis combined both descriptive and thematic analysis. Descriptive statistics were used to illustrate publication trends, geographic distributions, and methodological preferences. Thematic synthesis identified recurring AI approaches, application frameworks, and integration strategies for skill assessment and career pathway recommendations. Comparative evaluation highlighted the methodological strengths and weaknesses of the different approaches, as well as identifying gaps in current research and opportunities for future investigation. This synthesis provided a structured and evidence-based understanding of the current state of AI-powered frameworks in high school STEM and coding education.

4. RESULTS

4.1 Summary of Included Studies

By the PRISMA 2020 framework, 20 empirical studies met the inclusion criteria. Table 1 summarises the methodological and contextual features of these studies, detailing the AI techniques applied, recommendation strategies, application foci, geographic scope, and evaluation metrics, as mentioned in Table 1.

Table 1. Methodological and Contextual Characteristics of the 20 Included Studies on AI-Powered Skill Assessment and Career Pathway Recommendation in Secondary STEM and Coding Education

Source	AI Technique	Recommendation Approach	Application Focus	Country/Region	Evaluation Metrics	Education Level Focus	Dataset Source Type	Year of Publication
Ababneh et al. [17]	Machine Learning	Content-based Filtering	High school STEM skill prediction	Jordan	Accuracy, Precision, Recall	Upper Secondary	Institutional Records	2021
Abdalkareem & Min-Allah [18]	Explainable ML	Hybrid	Academic pathway prediction	Saudi Arabia	Accuracy, F1-score, Explainability metrics	Upper Secondary	National Education Database	2024
Ade & Deshmukh [19]	Machine Learning	Rule-based	Career choice prediction	India	Accuracy	Upper Secondary	School Surveys	2015
Alghamdi & Rahman [20]	Machine Learning	Content-based	Secondary school success prediction	Saudi Arabia	Accuracy, Recall	Secondary	Institutional Records	2023
Alsayed et al. [21]	Supervised Learning	Hybrid	Undergraduate major selection	Saudi Arabia	Accuracy, Precision	Upper Secondary	Institutional Records	2021
Chekalev et al. [22]	Machine Learning	Rule-based	Study direction choice	Russia	Accuracy	Upper Secondary	National Education Database	2022
El Haji & Azmani [23]	Big Data + AI	Hybrid	Educational and vocational guidance	Morocco	User satisfaction	Upper Secondary	Integrated Education Systems	2020
Goyal et al. [24]	Machine Learning	Chatbot Hybrid	Career counselling chatbot	India	User feedback, Accuracy	Secondary	Online Chatbot Interaction Logs	2023
Jawad et al. [25]	AI-assisted ML	Collaborative Filtering	Engineering program choice	USA	User engagement, Accuracy	Upper Secondary	Institutional Records	2023
Jimenez-Raygoza et al. [26]	Data Mining	Rule-based	Vocational guidance	Mexico	Accuracy	Upper Secondary	Institutional Records	2019
José-García et al. [27]	Machine Learning	Hybrid	Skill assessment + network visualization	Multiple (EU)	Accuracy, Visualization quality	Upper Secondary	Institutional Records	2023

Kiselev et al. [28]	Machine Learning	Collaborative Filtering	Professional identity construction	Russia	Accuracy	Upper Secondary	Social Network Data	2020
Lahoud et al. [29]	Recommender Systems	Hybrid	Major and career guidance	Lebanon	Precision, Recall	Upper Secondary	Institutional Records	2023
Liu & Tan [30]	AutoML	Content-based	STEM career prediction	Singapore	Accuracy, Explainability	Upper Secondary	Institutional Records	2020
Lou et al. [31]	Deep Learning	Content-based	STEM career forecasting	China	Accuracy, F1-score	Upper Secondary	Longitudinal Student Data	2023
Lutfiyani & Arifin [32]	Case-Based Reasoning	Rule-based	High school program recommendation	Indonesia	Accuracy	Upper Secondary	Institutional Records	2019
Mandalapu & Gong [33]	Data Mining	Collaborative Filtering	STEM career choice prediction	USA	Accuracy, Recall	Upper Secondary	School Surveys	2019
Mejía et al. [34]	Machine Learning	Hybrid	Multiple intelligence-based career guidance	Colombia	Accuracy, User feedback	Upper Secondary	Institutional Records	2021
VidyaShreeram & Muthukumaravel [35]	Machine Learning	Hybrid	Career prediction	India	Accuracy, Precision	Upper Secondary	Institutional Records	2021
Yadalam et al. [36]	Content-based Filtering	Content-based	Career recommendation system	India	Accuracy	Upper Secondary	Institutional Records	2020

4.2 Geographic Distribution of Included Studies

The geographic distribution of the 20 included studies is summarised in Table 2 and visualised in Figure 3. The Middle East and Asia-Pacific regions contributed the largest shares, with five studies each (25.0%). Europe accounted for three studies (15.0%), while Latin America and North America each contributed two studies (10.0%). Africa was represented by a single study (5.0%).

Table 2. Geographic Distribution of Included Studies

Region	Number of Studies	Percentage (%)
Middle East	5	25.0
Asia-Pacific	5	25.0
Europe	3	15.0
Latin America	2	10.0
North America	2	10.0
Africa	1	5.0

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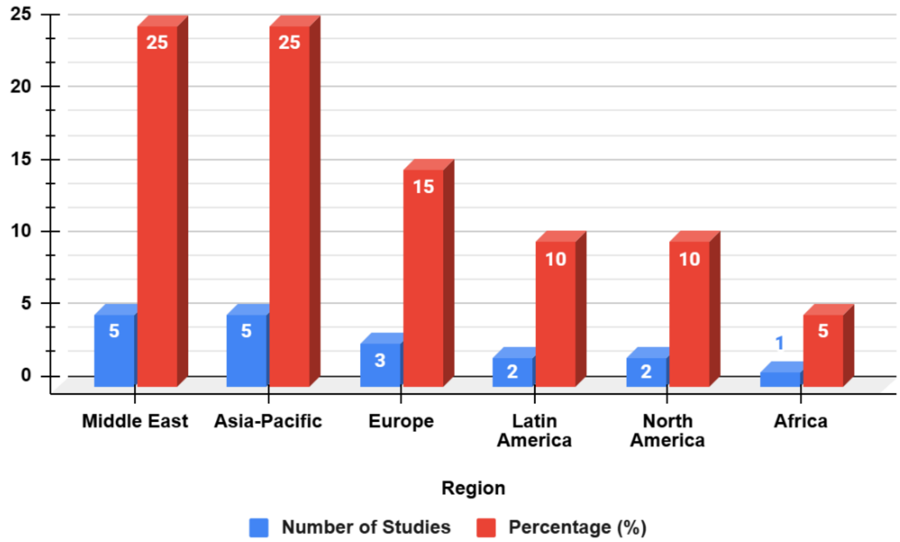

Figure 3. Regional Distribution of Included Studies on AI-Powered Skill Assessment and Career Guidance in Secondary STEM Education

Figure 3 illustrates the regional spread of the included studies. The Middle East and Asia-Pacific lead with equal representation at 25.0% each, followed by Europe at 15.0%. Latin America and North America each account for 10.0%, while Africa remains the most underrepresented region with 5.0%.

The geographic pattern highlights clear regional imbalances in AI-driven skill assessment and career pathway research for secondary education. Middle Eastern and Asia-Pacific studies are often driven by government-led STEM initiatives and large-scale education reforms. European contributions tend to emphasise methodological innovations, such as hybrid frameworks and multi-modal data integration. Latin America and Africa remain comparatively underrepresented, indicating gaps in research equity, infrastructure, and policy prioritisation. Addressing these disparities through cross-regional collaboration and validation studies will be essential to adapt AI models effectively across diverse socio-cultural contexts.

4.3 AI Techniques Utilized

Across the 20 included studies, Machine Learning, including variants such as supervised learning and AI-assisted ML was the dominant approach (n = 10, 50.0%). Other techniques were less frequently applied, including Data Mining (n = 2, 10.0%), Deep Learning (n = 1, 5.0%), Explainable Machine Learning (n = 1, 5.0%), AutoML (n = 1, 5.0%), Big Data + AI (n = 1, 5.0%), Case-Based Reasoning (n = 1, 5.0%), and Recommender Systems as a primary AI technique (n = 1, 5.0%). This distribution reflects a strong reliance on established supervised learning frameworks, likely due to their adaptability and compatibility with institutional datasets. More advanced and specialised approaches, such as deep learning, AutoML, and explainable AI, are emerging but remain underrepresented, suggesting future opportunities for methodological diversification in this domain.

Table 3. AI Techniques Used in Included Studies

AI Technique Category	Number of Studies	Percentage (%)
Machine Learning (incl. supervised & AI-assisted)	10	50.0
Data Mining	2	10.0
Deep Learning	1	5.0
Explainable Machine Learning	1	5.0
AutoML	1	5.0
Big Data + AI	1	5.0
Case-Based Reasoning	1	5.0
Recommender Systems (as primary AI technique)	1	5.0
Total	20	100.0

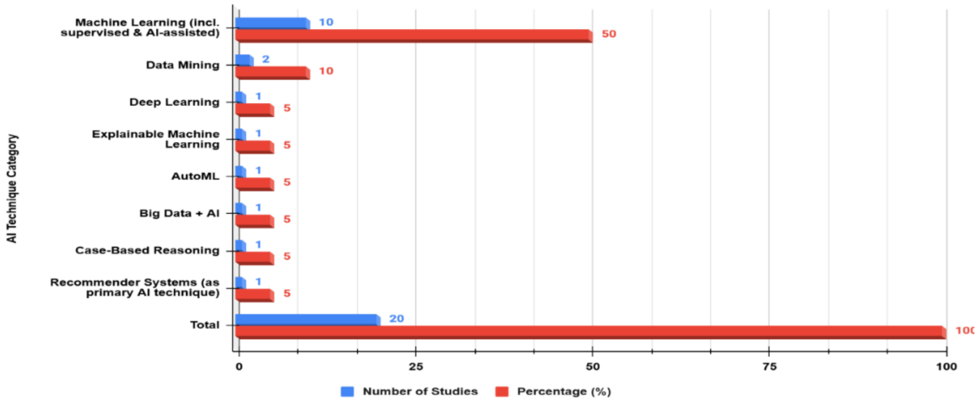

Figure 4. Distribution of AI Techniques Used in Included Studies on Secondary STEM Skill Assessment and Career Guidance

Figure 4 presents the proportional use of AI methodologies. Machine Learning dominates (50.0%), while other approaches, each at or below 10.0%, indicate a more experimental adoption pattern. The limited use of deep learning, explainable AI, and AutoML highlights methodological gaps and future research opportunities, particularly for improving transparency, scalability, and model adaptability in secondary education contexts.

4.4 Career Recommendation Approaches

Four primary recommendation approaches were identified across the 20 included studies (Table 4). Hybrid recommendation systems, often integrating collaborative filtering, content-based methods, and sometimes rule-based logic, were the most prevalent (n = 8, 40.0%). Content-based filtering was used in five studies (25.0%), while Rule-based approaches appeared in four studies (20.0%), typically in contexts prioritising transparency and the incorporation of domain expertise. Collaborative filtering was applied in three studies (15.0%), often in scenarios where historical user interaction data was available.

This distribution, visualised in Figure 5, indicates a growing preference for integrated hybrid frameworks that combine multiple recommendation strategies to improve personalisation and predictive accuracy, while still retaining the interpretability benefits of simpler rule-based methods in specific settings.

Table 4. Career Recommendation Approaches

Approach	Number of Studies	Percentage (%)
Hybrid Recommendation	8	40.0
Content-based Filtering	5	25.0
Collaborative Filtering	3	15.0
Rule-based	4	20.0
Total	20	100.0

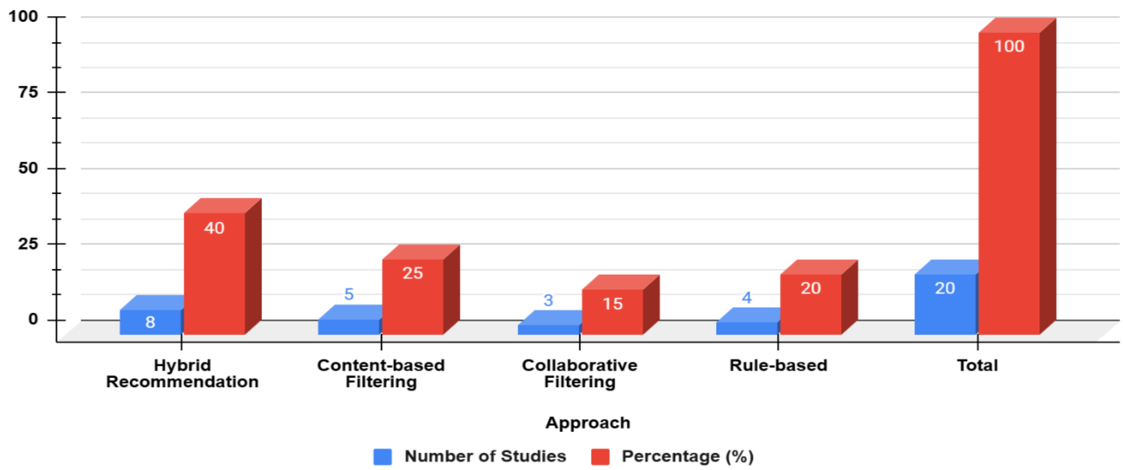

Figure 5. Distribution of Career Recommendation Approaches in Included Studies on Secondary STEM Education

Figure 5 illustrates the proportional use of different recommendation strategies. Hybrid systems lead with 40.0%, followed by content-based filtering (25.0%). Rule-based methods account for 20.0%, while collaborative filtering makes up 15.0%. The dominance of hybrid systems reflects the field's trend toward combining multiple algorithms to achieve both adaptability and accuracy in career pathway recommendations.

4.5 Evaluation Rigor and Methodological Trends

Evaluation strategies across the 20 included studies predominantly relied on quantitative performance metrics, with accuracy reported in 15 studies (75.0%). Other common measures included precision (n = 3, 15.0%), recall (n = 4, 20.0%), and F1-score (n = 2, 10.0%). These metrics reflect the strong emphasis on model performance benchmarking, particularly for classification and prediction tasks.

A subset of studies complemented these quantitative indicators with qualitative evaluation methods, capturing dimensions of system usability and learner experience. Examples include user satisfaction surveys, user feedback collection, and user engagement tracking through interaction logs. Such mixed-methods approaches help bridge the gap between algorithmic performance and real-world applicability in educational contexts.

The incorporation of explainable AI (XAI) marks an important methodological shift toward transparency, interpretability, and building stakeholder trust in AI-driven guidance systems. However, the limited adoption of XAI (10.0% of studies) suggests that explainability remains an emerging priority, with considerable scope for expansion in future research.

4.6 Regional Insights and Thematic Patterns

1. Middle East & Asia-Pacific: Studies from these regions (n = 10 combined) are frequently shaped by government-led STEM pipeline initiatives and national education reforms. They predominantly target skill-gap prediction, secondary-to-tertiary career pathway mapping, and early guidance interventions. Examples include STEM skill prediction in Jordan, academic pathway prediction in Saudi Arabia, and STEM career forecasting in China. Many leverage institutional or national education datasets, reflecting the regions' capacity for large-scale data integration.
2. Europe: Contributions from this region (n = 3) emphasise system integration, adaptive recommendation frameworks, and enhanced visualisation techniques. Approaches combine skill assessment with network-based visualisation to support learner profiling, while other work highlights the embedding of decision-support systems within broader educational contexts. Personalised recommendations are often achieved through collaborative filtering mechanisms.
3. North America: Contributions from this region (n = 2) indicate divergent priorities. Some emphasise usability, learner engagement, and adoption tracking, while others focus on algorithmic performance evaluation using quantitative metrics. Collectively, these approaches suggest a balance between technical optimisation and user-centred considerations in the regional research agenda.

4.7 Synthesis of Findings

The synthesis of evidence from the 20 included studies highlights several clear trends and gaps:
1. Machine Learning as the dominant foundation: Machine Learning, including supervised and AI-assisted variants, underpins half of all studies (n = 10, 50.0%), reflecting its adaptability and strong compatibility with institutional datasets. While Deep Learning is still relatively rare (n = 1, 5.0%), its presence signals early exploration of more complex architectures. The adoption of hybrid recommender systems (n = 8, 40.0%) indicates a growing preference for approaches that combine multiple algorithms to enhance adaptability and personalization potential.
2. Evaluation practices anchored in quantitative metrics: Most studies employ standard performance measures such as accuracy (75.0%), precision (15.0%), recall (20.0%), and F1-score (10.0%). A smaller subset incorporates qualitative measures, including user satisfaction, feedback, or engagement tracking, which help connect algorithmic outputs to learner experience.
3. Limited integration of explainable AI: Only two studies (10.0%) reported the use of explainability features, indicating that transparency and stakeholder trust are still emerging priorities. No studies in the dataset explicitly incorporated socio-emotional learning indicators, underscoring a methodological gap in capturing holistic learner needs.

4. Geographic concentration and collaboration opportunities: Research is concentrated in the Middle East (25.0%) and Asia-Pacific (25.0%), with fewer contributions from Europe (15.0%), Latin America (10.0%), North America (10.0%), and Africa (5.0%). This imbalance points to a need for cross-regional validation studies to ensure AI models are adaptable to diverse socio-cultural and educational contexts.

5. DISCUSSION

5.1 Interpretation of Results: Alignment with Research Objectives

This review examined the landscape of AI-powered frameworks for skill assessment and career pathway recommendation in secondary STEM and coding education. The findings align with the research objectives by mapping the predominant AI techniques, the types of career recommendation approaches, and the geographic distribution of studies. Machine Learning was the most frequently used technique (50.0%), reflecting adaptability and compatibility with institutional datasets. Hybrid recommender systems emerged as the leading approach (40.0%), indicating a preference for integrating multiple algorithms to enhance adaptability and personalization potential. The largest regional contributions originated from the Middle East and Asia-Pacific (25.0% each), reflecting targeted national education strategies, while European research showed a stronger emphasis on methodological innovation. Latin America (10.0%), North America (10.0%), and Africa (5.0%) were comparatively underrepresented, revealing persistent global participation gaps and highlighting the need for geographically balanced research in AI-enabled education.

5.2 Comparison with Previous Literature

The results align with earlier systematic reviews that identified Machine Learning as the dominant approach in educational AI applications. Unlike much of the prior work, which often concentrated on higher education, this synthesis exclusively examined the secondary and upper-secondary context, addressing unique challenges such as curriculum integration, adolescent learner needs, and constraints in student data access [37]. Compared with pre-2020 literature, there is a notable rise in hybrid recommender systems, which were less prevalent in earlier studies. Explainable AI remains relatively rare in the dataset (10.0% of studies), but its documented use marks a meaningful step toward addressing transparency and trust concerns that have been widely discussed in the field.

5.3 Pedagogical and Technical Implications

For Educators, AI-powered skill assessment tools can support differentiated instruction, early identification of at-risk learners, and more personalized STEM learning pathways. Hybrid recommendation frameworks can integrate curriculum-specific competencies with peer-comparison data, enabling tailored guidance for diverse student needs [38].

For Policymakers, the uneven regional representation observed highlights the need for policies that promote equitable access to AI in education. Key actions include investment in teacher training, development of ethical guidelines, and establishment of robust data governance protocols to ensure that AI deployments are contextually appropriate and inclusive, particularly in underrepresented regions.

For Developers and Researchers, the methodological diversity within the reviewed studies ranging from supervised Machine Learning to multi-modal hybrid recommenders' signals opportunities for improving robustness, scalability, and adaptability across contexts. Mainstreaming explainable AI should be prioritized to ensure that outputs are interpretable for educators, students, and guardians, and align with ethical AI governance frameworks [39].

5.4 Limitations

The scope of the review, while broad, was limited to Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and ERIC, potentially excluding relevant studies from regional or non-indexed journals, particularly in emerging research regions. Restricting the search to English-language publications may have excluded important contributions from countries where AI-in-education research is published in local languages, notably in Latin America, Africa, and parts of Asia. Dataset size and quality varied considerably across included studies; many relied on small, institution-specific datasets or lacked sufficient methodological transparency, limiting the generalizability of findings. Given the rapid pace of AI advancements, the results should be interpreted as a time-specific snapshot, with recognition that new models and applications will continue to emerge.

5.5 Future Research Directions

Future work should advance more sophisticated hybrid AI architectures that integrate Machine Learning, Deep Learning, and Natural Language Processing to enable richer multi-modal analyses of student performance and preferences [40]. Incorporating reinforcement learning may further enhance adaptability in dynamic learning environments. Explainable and interpretable AI should become standard practice, ensuring transparency and usability of recommendations for all stakeholders. Addressing current geographic imbalances is essential; cross-regional validation studies are needed to adapt models to diverse linguistic, cultural, and curricular contexts, particularly in underrepresented regions such as Latin America and Africa. Stronger integration of pedagogical theory into AI system design will ensure that technical outputs align with educational objectives. Finally, longitudinal research should evaluate the sustained impact of AI-driven career guidance on long-term STEM outcomes, including career entry, persistence, and achievement.

6. CONCLUSION

This systematic review synthesises research from 2010 to 2025 on AI-powered skill assessment and personalised career pathway recommendation in secondary-level STEM and coding education. The analysis confirms that Machine Learning remains the dominant AI technique (50.0%), with hybrid recommender systems as the most prevalent approach (40.0%), combining content-based and collaborative filtering to enhance adaptability and personalisation potential. Deep Learning is present but remains limited (5.0%), indicating early-stage adoption. Geographically, research output is concentrated in the Middle East (25.0%) and Asia-Pacific (25.0%), driven by national education reforms and government-backed STEM initiatives, followed by Europe (15.0%). Latin America and North America contribute 10.0% each, while Africa accounts for only 5.0%, underscoring a clear need for broader geographic representation and cross-regional validation to ensure AI model adaptability across diverse educational contexts. Pedagogically, the evidence highlights the capacity of AI tools to support differentiated instruction, early identification of skill gaps, and data-informed career decision-making. Technically, the limited but emerging use of explainable AI (10.0% of studies) represents an important step toward transparency and trust, though its integration remains far from standard practice. The findings are constrained by limitations in dataset size, methodological transparency, and language scope, which may affect generalisability. Future research should focus on developing multi-modal hybrid architectures that integrate Machine Learning, Deep Learning, and Natural Language Processing; expanding cross-cultural and cross-linguistic validation; embedding pedagogical theory into system design; and conducting longitudinal studies to evaluate sustained learning and career outcomes. The evidence reinforces AI's potential to transform career guidance in secondary STEM education, while emphasising that inclusivity, transparency, and pedagogical alignment are essential for equitable and effective future developments.

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