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Identification of Artificial Intelligence Tools in Learning and Human Resource Development: A Systematic Review

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ABSTRACT

Artificial intelligence is increasingly transforming learning and human resource development (HRD) by enhancing instructional design, personalized learning, performance analysis, and professional development. However, existing reviews have primarily classified AI according to underlying technologies rather than their functional roles in learning and HRD. This systematic review aimed to identify AI tools used in learning and HRD and develop a function-oriented taxonomy of their applications. Following the PRISMA 2020 guidelines, a systematic search was conducted across Scopus, Web of Science, and ScienceDirect. Twenty-five peer-reviewed studies published between 2007 and 2024 met the inclusion criteria. Methodological quality was assessed using the Mixed Methods Appraisal Tool (MMAT, 2018). AI technologies were first coded deductively using the framework of Votto et al. (2021), followed by an inductive thematic synthesis to develop a functional taxonomy. Natural language processing emerged as the dominant AI technology, while teacher professional development was the most frequently investigated application context. The analysis identified five functional categories of AI applications: instructional response and teaching analytics, natural language processing and text analytics, video processing, data management, and interactive and personalized learning. These findings indicate that AI primarily supports instructional feedback, reflective practice, adaptive learning, and evidence-informed decision-making across educational and organizational settings. This review contributes a function-oriented taxonomy that complements existing technology-based classifications and provides a practical framework for researchers, instructional designers, and HRD practitioners. It also highlights the limited evidence in organizational HRD and identifies priorities for future research on the implementation and long-term effectiveness of AI-supported learning environments. **©authors**

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1.Introduction

The use of artificial intelligence (AI) in organisations has gained increasing importance as a powerful tool for redesigning organisational processes, including human resource management and learning development (Malik et al., 2020). With capabilities such as autonomous learning and direct interaction with the environment, AI has brought unprecedented productivity and flexibility for learners and instructional designers (Stone et al., 2015). Studies have shown that integrating AI into educational processes, particularly in the field of workforce training and development, can make learning faster, more accurate, and more cost-effective (Bhatt & Muduli., 2023). For this reason, the use of AI to enhance learning and human resource development is expected to increase in the future (Kambur & Akar., 2022). In light of these considerations, it is essential to identify the applications of AI tools in designing learning opportunities and human resource development in order to improve practices related to organisational learning and development. Accordingly, the present study employs a systematic review method to examine opportunities for the use of AI tools in the design of learning opportunities and human resource development

Within the field of human resources, learning and development is defined as a comprehensive and long-term process aimed at improving individuals' capabilities, skills, and knowledge through planned learning and organisational experiences (Arulsamy et al., 2023). The introduction of emerging technologies into the field of education has created exceptional potential for learning and development. From learning management systems to AI-based tools that provide content personalisation and immediate feedback, these developments all reflect this transformation (Wang et al., 2024). Due to features such as data analysis, automated feedback, identification of learner needs, and facilitation of the learning process, AI has enabled substantial enhancement of the instructional design process in the domain of learning and human resource development (Chng., 2023). For example, machine learning algorithms can analyse data collected from learners, identify their training needs, and recommend appropriate content (Sandra et al., 2021).

Despite the growing significance of AI, systematic reviews of its applications in human resources have not been conducted extensively and have largely remained limited to areas such as the workplace, supply chains, business strategy, human resources, and recruitment (Bhatt & Muduli., 2023). In this regard, only a limited number of studies have systematically reviewed the application of AI tools in the field of learning and development. For instance, Fakhar et al. (2024) conducted a systematic review aimed at integrating AI into teachers' continuing professional development programmes. This study highlighted the importance of strengthening AI literacy among teachers as a key factor in the effective use of AI-based tools in educational settings. However, it did not provide a detailed analysis of the opportunities and challenges associated with such integration and focused primarily on its positive effects. In another study, Bhatt and Muduli (2023) examined the application of AI in learning and development processes. Their findings indicated that innovations such as natural language processing and bots can improve the efficiency of learning and development processes. However, their study did not provide a detailed examination or classification of AI tools.

In summary, the existing literature suggests that these studies have overlooked the identification of AI tools in the instructional design of learning opportunities and human resource development. Nevertheless, the literature also indicates that a considerable number of empirical studies have been conducted on the application of AI in learning and development, and a systematic analysis of these studies can offer up-to-date insights for stakeholders in this field (Zhai et al., 2021). Synthesising the findings of these studies through a systematic review constitutes a useful and comprehensive approach to examining opportunities in the design of learning and development (Bond et al., 2024; Grainger et al., 2020; Siontis & Ioannidis., 2018).

AI applications in learning and human resource development extend beyond technological capabilities to support diverse educational functions such as personalized learning, assessment, feedback, analytics, and instructional decision-making. Although previous studies have classified AI primarily according to technical characteristics, a functional perspective is needed to better explain how AI supports learning and HRD processes. This review addresses this need by developing a function-oriented taxonomy of AI applications.

Accordingly, this study aims not only to systematically identify AI tools used in learning and human resource development but also to develop a function-oriented taxonomy that synthesizes how these tools support educational and organizational learning processes. By integrating technical AI classifications with an inductive functional analysis, this review offers a conceptual framework that extends beyond descriptive evidence and provides practical guidance for future research and implementation. The findings of this study may assist managers, decision-makers, researchers, academics, and educational professionals in identifying the most effective strategies and practices for integrating AI into educational environments.

2.Method

The present study is a systematic review that employed a qualitative research approach to examine existing studies focused on identifying artificial intelligence tools used in designing learning opportunities and supporting the professional development of the workforce. A qualitative systematic review was considered the most appropriate methodological approach because the included studies differed considerably in terms of research design, AI technologies, learning contexts, and reported outcomes. Such heterogeneity limited the feasibility of quantitative synthesis. A qualitative synthesis allowed not only the systematic integration of evidence but also the inductive development of a function-oriented taxonomy of AI applications and the identification of research trends and gaps across learning and human resource development contexts. This review was based on information extracted from peer-reviewed articles indexed in three reputable international databases, Web of Science (WoS), Scopus, and EBSCO, using predefined search keywords.

2.1 Articles Identification

Initially, precise search strings were developed. To ensure comprehensiveness, a set of synonyms was identified for the key concepts of the study. These synonyms were drawn from credible sources, including peer-reviewed academic literature. Boolean operators, namely AND and OR, were then strategically used to combine these keywords. This rigorous approach was adopted to maximise the scope of the search results. Within the domain of artificial intelligence, keywords such as “artificial intelligence”, “AI”, “intelligent support”, “intelligent virtual reality”, “chat bot”, “machine learning”, “intelligent agent”, and “natural language processing” (Zawacki-Richter et al., 2019) were selected. For the domain of professional development, the keywords “learning and development”, “L&D”, “professional development” (Bhatt & Muduli., 2023), “employee training”, “staff training”, “human training”, “human resource development”, “employee development”, and “staff development” were included. The complete search strategies for all databases are provided in Supplementary-Material-Appendix-1.

2.2 Inclusion and exclusion criteria

Articles published between 2007 and 2024 were screened according to the inclusion and exclusion criteria presented in Table 1. Studies published in or after 2007 were included because this was the year in which Siri, an algorithm-based personal assistant originally developed as part of a Defence Advanced Research Projects Agency (DARPA)-funded AI project and later acquired by Apple, was introduced (Zawacki-Richter et al., 2019).

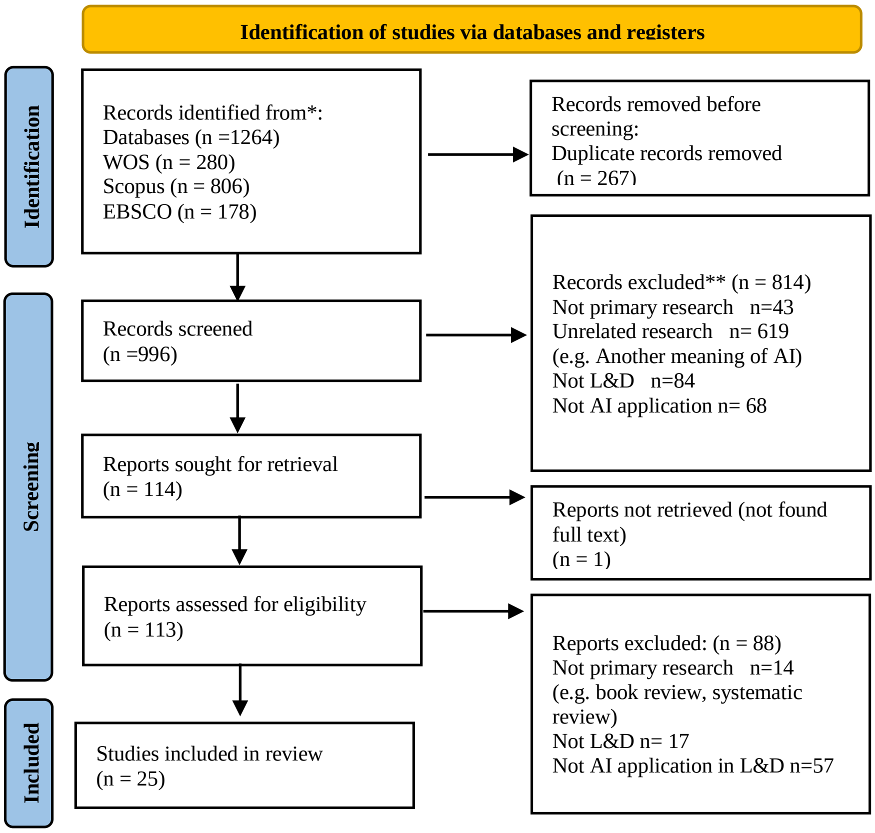
Table 1. Inclusion and exclusion criteria

Exclusion	Inclusion
Does not include "artificial intelligence" or one of its subcategories in the title, abstract, or author keywords.	The article includes "artificial intelligence" or one of its subcategories in the title, abstract, or author keywords.
Not written in English.	Written in English.
Not published in a reputable journal or peer-reviewed conference.	Published in a reputable journal or peer-reviewed conference.
Not published between 2007 and 2024	Published between 2007 and 2024.
Non-empirical studies (e.g., reviews).	Primary or empirical research.
Not related to workforce professional development.	Concerned with workforce professional development.

2.3 Article screening and inclusion

The PRISMA flow diagram (Haddaway et al., 2022) was used to illustrate the screening process, including the identification, screening, eligibility assessment, and final selection of studies (Martin et al., 2023). As shown in Figure 1, keywords were searched in each database according to its specific settings, and filters related to time frame, language, and article type were applied based on the inclusion and exclusion criteria. In the identification stage, 280 articles were retrieved from Web of Science, 806 from Scopus, and 178 from EBSCO, resulting in a total of 1,264 records. Duplicate articles were removed using Mendeley (version 1.18.9), yielding 996 articles for screening. The next phase, conducted using Rayyan software, involved a two-stage screening of titles and abstracts, resulting in 114 articles selected for full-text analysis. After reviewing the full texts, 25 articles were ultimately included in the final analysis.

Figure 1. *Flowchart of article selection*



2.4 Data Coding and Thematic Synthesis

A structured coding framework was developed to systematically extract and synthesize data from the included studies. The extracted information comprised article characteristics (publication year, journal, authors' countries, first author's academic discipline, research method, intervention duration, and AI tool), participant characteristics (age, gender, occupation, and educational background), AI-related characteristics (underlying AI technique, AI tool or system, and mode of application), as well as the reported learning context, opportunities, challenges, and outcomes associated with AI implementation.

Data analysis followed a hybrid deductive–inductive coding strategy. In the first stage, AI tools and systems identified in the included studies were deductively coded according to the technical taxonomy proposed by Votto et al. (2021), which classifies AI technologies into four principal categories: Machine Learning, Natural Language Processing (NLP), Computer Vision, and Recommender Systems. This stage aimed to identify the underlying computational techniques supporting each AI application while ensuring consistency in the technical classification of the extracted evidence.

In the second stage, a qualitative thematic synthesis was conducted to examine the functional roles of AI applications within learning and human resource development contexts. Initially, descriptive codes were assigned to each study based on the reported AI technique, AI tool or system, educational application, and intended function. Through an iterative process of constant comparison, conceptually similar applications were refined and grouped into higher-order categories according to their dominant function rather than their underlying computational technology. This inductive analysis resulted in the development of five functional categories that form the analytical framework presented in the Findings section. Consequently, while the taxonomy proposed by Votto et al. (2021) informed the initial technical coding, the final taxonomy represents an evidence-driven functional classification derived inductively from the reviewed studies rather than a direct adoption of an existing AI classification framework.

To enhance coding reliability, half of the included studies were independently coded by two researchers. The coding results were subsequently compared, and disagreements were resolved through discussion until consensus was reached. Interrater reliability was assessed using Cohen’s kappa coefficient, yielding a value of 0.79, which indicates substantial agreement between the coders.

2.5 Validity and reliability

Reliability is essential for minimising bias in systematic review procedures. Strategies used to enhance reliability in this review included clearly defined inclusion and exclusion criteria, the use of a standardised coding form for data extraction, and detailed documentation of methods to allow replication. Validity is equally important for ensuring that the results are meaningful; therefore, clearly defined research questions, transparent reporting of methods, and the use of multiple databases to identify studies were employed as strategies to strengthen validity.

The complete coding framework, including both the technical coding and the extracted functional codes, is provided in Supplementary_material_appendix-2 for transparency and reproducibility.

2.6 Quality Assessment

A methodological quality assessment was conducted using the Mixed Methods Appraisal Tool (MMAT, 2018 version), which is suitable for evaluating qualitative, quantitative, and mixed-methods studies within a single review. Each included study was assessed with regard to the clarity of research objectives, appropriateness of methodology, adequacy of data collection procedures, transparency of analysis, consideration of ethical issues, and coherence between data and conclusions.

Two researchers independently assessed a subset of the included studies and resolved any disagreements through discussion until consensus was reached. The quality assessment was used to inform the interpretation of findings rather than as a basis for excluding studies. Overall, most studies demonstrated acceptable methodological quality, although several studies showed limitations related to sample size, reporting transparency, and generalizability.

3. Findings

The review included 25 studies published between 2007 and 2024. To provide an overview of the evidence base, descriptive analyses were conducted regarding publication trends, geographical distribution, research contexts, and AI technologies represented in the included studies.

The trend illustrated in Figure 2 indicates a substantial increase in the number of studies investigating the application of artificial intelligence in professional development, particularly from 2022 through June 2024. This upward trajectory suggests that AI has rapidly gained recognition as a strategic tool for addressing diverse challenges and enhancing processes within professional development contexts. The growing volume of research reflects the increasing adoption and significance of AI technologies in supporting learning, performance improvement, and workforce development initiatives.

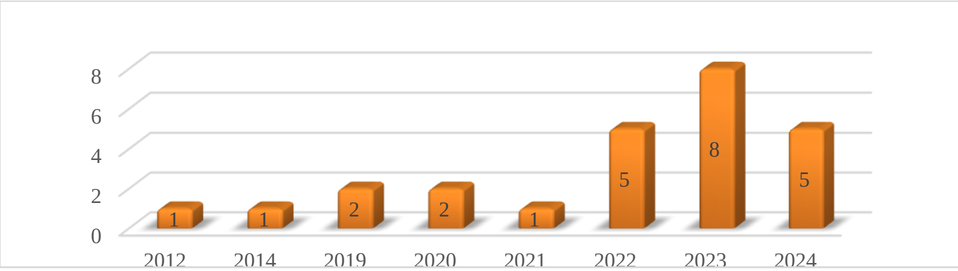


Figure 2. *Annual distribution of included studies by publication year*

Figure 3 illustrates that the United States contributed the largest number of studies on the application of artificial intelligence in professional development, followed by China and Germany. This pattern may be attributed to these countries' strong research capacity, substantial funding support, and the presence of leading universities and research institutions. Several European countries, including Germany and Slovenia, have also contributed to this field, although to a more limited extent. Overall, the geographical distribution of the included studies indicates that research on AI in professional development has been concentrated predominantly in technologically advanced countries with well-established research infrastructure.

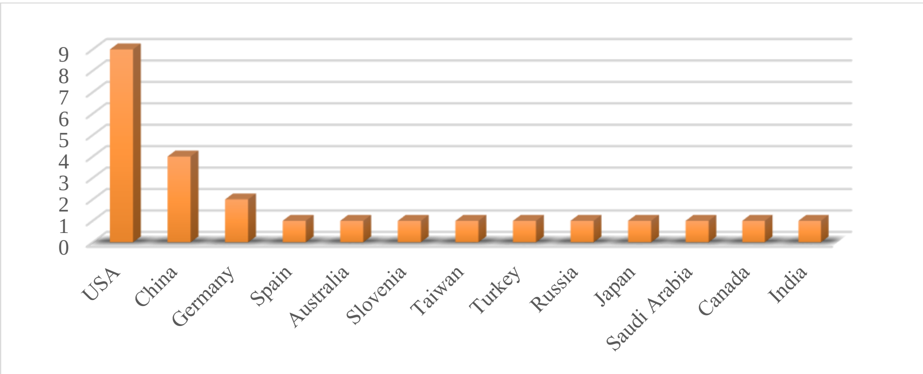


Figure 3. *Geographical distribution of the included studies by country*

Figure 4 presents the primary types of artificial intelligence employed across the included studies. Although several studies incorporated multiple AI technologies, only the predominant AI type used in each study was considered for this analysis. The findings indicate that Natural Language Processing (NLP) was the most frequently applied AI technology. NLP focuses on the representation, processing, understanding, and generation of human language through computational methods. In the reviewed studies, NLP techniques were primarily used to develop intelligent writing assistants, automated assessment systems, and computer-based intelligent tutoring systems, many of which rely on natural language understanding (NLU), a subfield of NLP (Woolf et al., 2021). Machine learning and the use of general-purpose AI tools were the second and third most frequently employed AI technologies, respectively.

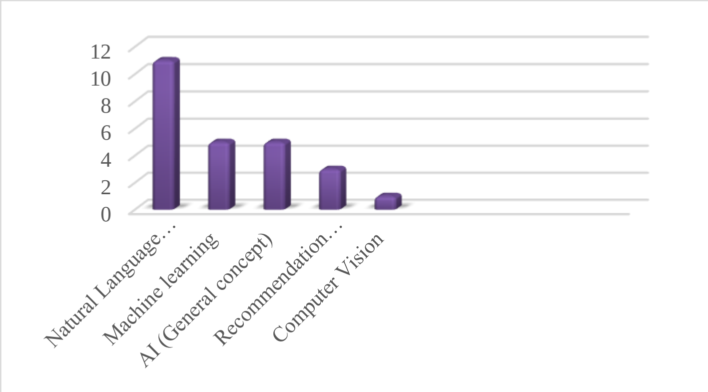


Figure 4. *Primary AI technologies identified in the included studies*

Although the review adopts a learning and human resource development (HRD) perspective, the included studies were not limited to organizational HRD settings. A substantial proportion of the evidence (15 of 25 studies) examined AI applications in teacher professional development, while the remaining studies investigated learning and development practices in broader organizational contexts. This distribution reflects the interdisciplinary nature of learning and HRD research and broadens the applicability of the proposed taxonomy across both educational and workplace learning environments. This imbalance indicates that AI-supported HRD research is still emerging outside educational contexts.

Although AI tools were initially classified according to their underlying technologies using the framework of Votto et al. (2021), the primary objective of this review was to understand how these tools support learning and human resource development. Therefore, following the initial deductive coding, an inductive thematic synthesis was conducted to identify common functional roles across the reviewed studies. This analysis resulted in a functional taxonomy consisting of five categories, presented below.

The artificial intelligence (AI) tools employed in the reviewed studies can be categorised into five overarching groups based on their primary applications: (a) instructional response and teaching analytics tools, (b) natural language processing and text analytics tools, (c) video processing and feature analysis tools, (d) data management and organisational development systems, and (e) interactive and personalised learning tools. The resulting taxonomy represents one of the principal contributions of this review by providing a functional classification of AI applications across learning and human resource development contexts. Table 2 presents the classification of these tools according to their application domains.

Table 2*. Functional Taxonomy of AI Tools in Learning and Human Resource Development Developed through Hybrid Deductive–Inductive Analysis*

Functional Category	Underlying AI Technique(s)	Representative AI Tools / Systems	Primary Function in Learning & HRD
Instructional Response and Teaching Analytics	NLP, Machine Learning	TRT, M-Powering Teachers, Language Muse	Lesson planning, instructional feedback, teacher reflection, teaching analytics
Natural Language Processing and Text Analytics	Natural Language Processing (NLP)	ChatGPT, Speech-to-Text System, Language Muse (Reflection Analysis Tools)	Text generation, summarization, reflective writing analysis, feedback generation

Video Processing	Computer Vision	OpenPose, Video Feature Extraction Algorithms	Classroom observation, teacher behavior recognition, instructional performance analysis
Data Management	Machine Learning	K-Means Clustering, Machine Learning Models, AI-based HRD Systems	Training needs analysis, learner segmentation, employee profiling, decision support
Interactive and Personalised Learning	Recommender Systems, NLP, Machine Learning	Intelligent Tutoring Systems (ITS), OPD Program, nBrowser	Personalized learning pathways, adaptive feedback, professional development support

3.1 Instructional Response and Teaching Analytics

Artificial intelligence applications within this category primarily employed natural language processing (NLP) to support teachers' instructional decision-making through automated feedback, classroom discourse analysis, and text-based instructional support. Across the reviewed studies, these tools were designed to augment teachers' professional practice by providing evidence-informed recommendations rather than replacing teacher judgement. Although the systems differed in their specific objectives, they consistently focused on improving instructional responsiveness, reflective practice, and lesson design.

3.1.1 Teacher Responding Tool (TRT)

The Teacher Responding Tool (TRT) applies natural language processing to analyse students' written mathematical explanations and generate multiple feedback suggestions that teachers can review, modify, and personalise before responding to learners. Rather than communicating directly with students, the system functions as a teacher-support tool that assists educators in recognising subtle differences in students' mathematical thinking and developing more appropriate instructional responses (Bywater et al., 2019).

3.1.2 Automated Feedback Tools for Teachers (Teacher Empowerment Tools)

Similarly, the M-Powering Teachers system developed by Demszky et al. (2023) employs NLP techniques to analyse classroom dialogue and provide automated feedback on teachers' uptake of students' ideas during classroom interactions. The system evaluates how teachers acknowledge, build upon, and respond to students' contributions while providing supportive, non-evaluative recommendations and examples of effective instructional practices. Unlike resource-intensive human coaching, the platform was designed to deliver scalable and low-cost feedback suitable for large numbers of teachers and online professional development environments (Demszky et al., 2023).

3.1.3 Text Analysis and Feedback Tool: Language Muse (LM)

Language Muse represents another NLP-based application that supports teacher professional development through automated linguistic analysis and instructional design. Across two related studies, the system was used to assist teachers in identifying linguistic complexities within instructional texts, thereby supporting the development of learning materials for English language learners (Burstein et al., 2012, 2014). The platform provides automated feedback at multiple linguistic levels, including lexical, idiomatic, sentential, and discourse features, allowing teachers to revise instructional materials according to learners' language needs. In its later development, Language Muse was extended into a web-based professional development environment that integrated automated linguistic feedback with online instructional resources, videos, and lesson-planning support to facilitate flexible teacher learning (Burstein et al., 2014).

Across these studies, instructional response and teaching analytics applications consistently employed AI to support teachers' professional judgement through automated feedback, instructional analytics, and evidence-based recommendations rather than replacing instructional decision-making. Although the reviewed tools addressed different aspects of teaching practice, including mathematical feedback, classroom discourse, and language-focused instruction, they shared a common objective of strengthening teachers' reflective practice and improving the quality of instructional interactions (Bywater et al., 2019; Burstein et al., 2012, 2014; Demszky et al., 2023).

3.2 Natural Language Processing and Text Analytics

Natural language processing (NLP) and text analytics represented the most extensively investigated category of AI applications across the reviewed studies. Unlike the previous category, which focused primarily on instructional decision support, NLP-based applications were employed across a broader range of learning and HRD functions, including content generation, lesson planning, brainstorming, reflective writing, automated feedback, learning analytics, speech analysis, and training needs assessment. Although different AI techniques and systems were employed, the reviewed studies consistently demonstrated the growing role of language-based AI in supporting both educational and organizational learning processes.

3.2.1 ChatGPT

ChatGPT emerged as the most frequently investigated generative AI tool in recent studies of learning and human resource development. Across the reviewed studies, ChatGPT was primarily used to support lesson planning, content generation, brainstorming, reflective practice, instructional feedback, and professional learning (Li et al., 2024; Ardichvili et al., 2024; Lu et al., 2024; Chang et al., 2024).

In educational contexts, ChatGPT supported pre-service teachers and instructors by facilitating lesson preparation, integrating instructional resources, promoting interdisciplinary learning, stimulating creative thinking, and improving the efficiency of learning activities (Li et al., 2024; Lu et al., 2024). Several studies also reported its use in generating simulated learner responses, enabling educators to explore alternative classroom scenarios and strengthen instructional planning (Lu et al., 2024). Within clinical education, ChatGPT was employed to generate responses to authentic teaching scenarios that educators subsequently evaluated against established academic evidence, supporting reflective analysis and critical evaluation of AI-generated content (Chang et al., 2024).

In organizational HRD contexts, ChatGPT primarily functioned as a planning and ideation support tool. Participants used the system during brainstorming, intervention design, and the development of HRD programmes, particularly during the early stages of project planning (Ardichvili et al., 2024). However, the reviewed evidence also identified several limitations. AI-generated outputs frequently required expert review and contextual adaptation because they lacked sufficient understanding of complex organizational environments. Studies additionally highlighted concerns related to contextual accuracy, validation of AI-generated recommendations, and data privacy when organizational information was incorporated into AI-supported workflows (Ardichvili et al., 2024).

Collectively, these studies indicate that ChatGPT is increasingly employed as a cognitive support tool that complements, rather than replaces, educators' and HRD professionals' expertise. Across educational and organizational settings, its principal applications included idea generation, instructional planning, content development, feedback support, and reflective learning (Li et al., 2024; Ardichvili et al., 2024; Lu et al., 2024; Chang et al., 2024).

3.2.2 Speech-to-Text Systems

Speech-to-text technologies were applied to transform spoken instructional interactions into analysable textual data for learning analytics and instructional evaluation. Phillips et al. (2023) developed a customised AI toolkit that combined natural language processing, bidirectional long short-term memory (BiLSTM) neural networks, word embeddings, automated speech recognition, and learning management system data to analyse classroom instruction. Rather than relying on commercially available generative AI systems, the study implemented a purpose-built AI model capable of processing large volumes of lecture transcripts and assessment data to support continuous instructional feedback and educational analytics (Phillips et al., 2023).

3.2.3 Machine Learning Models

Machine learning models were primarily employed to automate the evaluation of reflective writing and analyse complex textual datasets for professional learning assessment. The reviewed study demonstrated that AI-based scoring models could automatically evaluate reflective writing while substantially reducing the time and effort required for qualitative coding and assessment (Mientus et al., 2023). In addition to automated evaluation, machine learning enabled personalised feedback based on textual analysis and learner behaviour, while supporting more consistent and standardised assessment procedures for professional development programmes (Mientus et al., 2023).

3.2.4 K-Means Clustering Algorithm

The K-means clustering algorithm was identified as a machine learning technique for analysing employee performance data and supporting training needs assessment within human resource development. By clustering employees according to similarities in knowledge, skills, abilities, and other characteristics (KSAOs), the algorithm enabled organisations to identify workforce development priorities and optimise professional development planning (Escolar-Jimenez et al., 2019).

3.2.5 AI-Based Digital Platforms for Reflective Learning

Several studies employed AI-based digital platforms to support reflective learning through automated analysis of participants' written reflections and personalised feedback generation. These platforms analysed reflective writing to identify learning patterns, support professional reflection, and facilitate the design of more targeted development programmes (Cohen et al., 2023).

Similarly, machine learning techniques were applied to automate the evaluation of reflective writing in educational and professional development settings, thereby reducing dependence on manual assessment while enabling large-scale feedback delivery (Barthakur et al., 2022). Wulff et al. (2021) further demonstrated the use of natural language processing together with machine learning algorithms, including multinomial logistic regression and decision trees, to classify teachers' reflective writing and generate structured analytical feedback that supported professional learning.

Across these studies, AI-based reflective learning platforms consistently integrated natural language processing and machine learning techniques to support reflective practice through automated feedback, scalable assessment, and analysis of written reflections. Although the platforms differed in their technical implementation, they shared the common objective of enhancing reflective learning while reducing the workload associated with manual evaluation (Barthakur et al., 2022; Cohen et al., 2023; Wulff et al., 2021).

Across the reviewed studies, natural language processing emerged as the dominant AI technology supporting learning and human resource development. While earlier studies primarily employed task-specific NLP applications for linguistic analysis, reflective writing, and instructional feedback, more recent research increasingly incorporated generative AI tools, particularly ChatGPT, to support broader instructional, organizational, and professional learning activities. Collectively, the evidence demonstrates a clear evolution from specialised language-processing applications toward more comprehensive AI-supported learning environments that integrate content generation, feedback, analytics, and reflective practice.

3.3 Video Processing

3.3.1 Computer Vision Tools (OpenPose)

Video processing applications primarily employed computer vision techniques to analyse instructional videos and extract behavioural information from classroom interactions. Across the reviewed studies, these applications focused on analysing teachers' instructional behaviours, classroom performance, and professional practice through automated processing of visual data.

The reviewed study employed OpenPose to extract teachers' body-skeleton data from classroom videos and combined these data with support vector machine (SVM) algorithms to classify instructional behaviours based on movement and posture characteristics (Wu et al., 2020). By integrating computer vision with machine learning techniques, the system enabled automated analysis of classroom videos and generated structured information regarding teachers' instructional practices.

In addition to skeletal tracking, the integration of multimodal data, including RGB video and skeletal movement information, improved the accuracy of behavioural recognition and supported more comprehensive analysis of classroom interactions (Wu et al., 2020). The system also generated individual behavioural reports and automated feedback based on teachers'observed instructional patterns, providing evidence to support professional reflection and instructional evaluation.

Compared with the other functional categories identified in this review, video-processing applications appeared less frequently and were primarily implemented to analyse teaching practices and classroom interactions. Across the reviewed evidence, computer vision technologies were mainly applied to classroom observation, behavioural analysis, instructional performance assessment, and professional reflection. Overall, these findings indicate that computer vision currently represents a complementary AI application that supports evidence-based evaluation of teaching practices within professional development programmes (Wu et al., 2020).

3.4 Data Management

Data management applications primarily employed machine learning and predictive analytics to analyse educational and workforce data, generate personalised recommendations, and support evidence-based decision-making in learning and human resource development. Across the reviewed studies, AI systems focused on modelling learner and employee characteristics, predicting future behaviours, and facilitating the design of adaptive learning and professional development strategies.

3.4.1 Machine Learning and Neural Networks in Database Management Systems (MySQL)

Machine learning algorithms and neural networks were employed to personalise employee learning pathways through the analysis of user profiles, learning interactions, and professional characteristics (Morozevich et al., 2022). The reviewed study integrated matrix factorisation techniques and neural networks into a MySQL database management system, enabling the generation of personalised learning recommendations and prediction of employees' learning behaviours.

The intelligent database system continuously adapted learning pathways according to employees' personal profiles and responses to instructional activities while analysing both technical competencies and soft skills. The system also supported the development of T-shaped professionals by integrating specialised expertise with broader professional competencies. In addition, personalised recommendations enabled employees to engage in learning activities aligned with their individual interests and professional capabilities (Morozevich et al., 2022).

3.4.2 AI-Driven Human Resource Development Systems

Machine learning was also applied to predict instructors' long-term engagement with online teaching and support professional development planning. Shi and Guo (2022) analysed behavioural data collected through the Rain Classroom platform to develop predictive models capable of identifying instructors who were likely to continue using online teaching after the COVID-19 pandemic.

The predictive models identified patterns associated with sustained online teaching and highlighted professional roles and instructional activities related to continued technology adoption. Model outputs were further used to identify instructors' professional learning needs and support the design of more personalised development programmes. The analysis also identified competencies associated with successful technology integration, including learning assessment and technology facilitation, providing evidence to inform professional development planning (Shi & Guo, 2022).

Across the reviewed studies, AI-supported data management systems consistently employed machine learning techniques to analyse educational and workforce data, predict learning behaviours, and generate personalised recommendations for professional development. Rather than supporting direct instructional interaction, these applications primarily functioned as decision-support systems that informed learning management, workforce development, and evidence-based HRD planning through predictive analytics and intelligent data modelling (Morozevich et al., 2022; Shi & Guo, 2022).

3.5 Interactive and Personalised Learning

Interactive and personalised learning applications represented AI systems that dynamically adapted learning experiences according to users' responses, learning progress, and professional development needs. Across the reviewed studies, these applications combined natural language processing, intelligent tutoring, adaptive learning, and learning analytics to provide personalised feedback, facilitate reflective learning, and support continuous professional development. Although the systems differed in their instructional designs, they consistently emphasised learner-centred interaction and adaptive instructional support.

3.5.1 Asynchronous Interactive and Personalised Programme

One group of studies examined asynchronous AI-supported professional development environments that provided personalised feedback through virtual facilitators. The Online Professional Development (OPD) programme employed natural language processing to analyse teachers' responses to professional development activities and deliver individualised feedback aimed at strengthening both content knowledge (CK) and pedagogical content knowledge (PCK) in mathematics education (Copur-Gencturk, Li, Cohen, et al., 2024).

The reviewed study demonstrated that the AI-supported programme continuously analysed teachers' responses and generated adaptive feedback without requiring direct intervention from human coaches. The virtual facilitator supported teachers throughout professional learning activities while maintaining confidential interactions between participants and the system. The programme was implemented as an asynchronous learning environment capable of providing personalised feedback throughout teachers' professional development process (Copur-Gencturk, Li, Cohen, et al., 2024).

3.5.2 Intelligent Tutoring Systems (ITS)

Intelligent Tutoring Systems (ITS) represented another form of adaptive AI application designed to support teachers through interactive dialogue and personalised instructional guidance. The reviewed ITS employed the Expectations and Misconceptions Tracking (EMT) framework, using natural language processing to analyse teachers' responses and dynamically adapt instructional prompts according to individual performance (Copur-Gencturk et al., 2024).

The dialogue-based architecture enabled continuous interaction between teachers and the AI system while providing immediate feedback throughout learning activities. Adaptive feedback was generated according to users' responses to support formative assessment and guide teachers toward achieving the instructional objectives embedded within each professional learning activity (Copur-Gencturk et al., 2024).

3.5.3 Self-Improving Intelligent Tutoring Systems

Adaptive learning was further extended through self-improving intelligent tutoring systems capable of refining recommendations based on users' learning behaviours. Huang et al. (2022) investigated the nBrowser platform, a web-based instructional system designed to support teachers' self-regulated learning, curriculum planning, technology integration, and use of open educational resources.

The self-improving system analysed users' interactions and continuously refined its recommendations to provide increasingly personalised instructional support. Teachers using the platform demonstrated improvements in self-regulated learning, instructional planning, technology-integrated curriculum design, and strategic selection of educational resources. The study also reported stronger pedagogical knowledge among teachers who used the adaptive system compared with those who did not participate in the self-improving learning environment (Huang et al., 2022).

Across the reviewed studies, interactive and personalised learning systems consistently employed adaptive AI technologies to personalise professional learning through continuous analysis of learner responses and dynamic feedback generation. Although the reviewed applications differed in their implementation, including virtual facilitators, dialogue-based intelligent tutoring systems, and self-improving adaptive platforms, they shared the common objective of supporting personalised learning, reflective practice, and continuous professional development through adaptive instructional interaction (Copur-Gencturk et al., 2024; Copur-Gencturk, Li, Cohen, et al., 2024; Huang et al., 2022).

Across the reviewed studies, AI applications in this category focused on adapting learning experiences to individual learner needs through personalized recommendations, feedback, and instructional support. Although different technologies were employed, all shared the objective of increasing learner engagement and improving learning effectiveness. Overall, the findings demonstrate that personalization has become a central function of AI in both educational and HRD contexts.

4. Discussion

This review extends previous research by proposing a functional taxonomy of artificial intelligence applications in learning and human resource development. Unlike previous reviews, which have primarily classified AI according to computational techniques such as machine learning, natural language processing, computer vision, and recommender systems, the taxonomy developed in this review organizes AI tools according to their functional roles in educational and organizational contexts. By adopting this function-oriented perspective, the proposed taxonomy provides a more practice-oriented framework for understanding how AI technologies support professional learning, instructional improvement, organizational development, and personalized learning, while offering researchers and practitioners a practical basis for aligning AI applications with educational and organizational objectives.

In the first category, instructional response and teaching analytics, evidence suggests that AI can function as both a coaching assistant and an educational analyst. These tools can optimise employees' learning pathways by analysing instructional practices, the quality of workplace interactions, and real-time feedback (Demszky et al., 2023). Through data-driven insights, AI shifts the role of trainers and instructional leaders from direct supervision toward strategic facilitation and data-informed decision-making.

The second category, natural language processing (NLP) and text analytics, emerged as the broadest area of application within HRD. These tools enable the extraction of key skills, learning needs, and performance gaps through the analysis of dialogues, reports, résumés, and various organisational documents. Collectively, these findings indicate that NLP is evolving from a text-processing technology into a strategic component of professional learning and evidence-informed HRD planning (Phillips et al., 2023).

The third category, video processing, plays a significant role in assessing behavioural and communication skills. These AI tools can detect non-verbal behaviours, presentation styles, interaction patterns, and other behavioural indicators, thereby offering more precise feedback than traditional observational methods (Wu et al., 2020). These findings highlight the growing importance of multimodal evidence in professional development, where behavioural analytics can complement traditional observation-based evaluation.

In the fourth category, data management, AI's role in analysing large-scale HR data and predicting workforce trends was particularly prominent. By monitoring performance metrics, job satisfaction, turnover patterns, and emerging skill sets, these systems provide a more accurate and strategic understanding of organisational health. The results indicate that such systems not only support improved career planning but also facilitate the design of more equitable and tailored professional growth pathways (Morozevich et al., 2022).

Finally, the fifth category, interactive and personalised learning, demonstrated the most direct impact on skill development. Adaptive systems, simulators, and interactive platforms allow employees to engage in deeper learning experiences and progress according to their individual needs. Evidence shows that these tools enhance learning motivation, accelerate progress, and increase the transfer of learning to workplace contexts (Huang et al., 2022).

The proposed taxonomy represents a conceptual contribution to the literature by shifting the focus from technology-centered classifications toward function-oriented categorization. Existing AI taxonomies typically distinguish technologies such as machine learning, natural language processing, or computer vision. While these classifications describe how AI systems operate, they provide limited insight into how AI supports learning and human resource development processes. In contrast, the taxonomy developed in this review organizes AI applications according to their educational functions, thereby offering a more practice-oriented framework for researchers, instructional designers, and HRD practitioners.

This function-oriented perspective may facilitate future comparative studies, support instructional design decisions, and provide a conceptual foundation for evaluating emerging AI technologies beyond specific tools such as ChatGPT.

One important finding of this review is the uneven distribution of evidence across learning and HRD contexts. While AI applications have been widely investigated in teacher professional development and higher education, comparatively little empirical evidence exists regarding workplace learning, organizational development, leadership training, or corporate HRD. Consequently, the findings of this review should be interpreted primarily in light of the current evidence base rather than as representing the entirety of HRD practice.

Although the reviewed studies consistently report promising applications of AI, the available evidence is not yet sufficient to conclude that AI has fundamentally transformed or matured the field of HRD. Rather, the findings suggest an ongoing transition toward broader AI integration.

5. Conclusion

The five-category classification presented in this review provides a comprehensive perspective on the roles that AI technologies play in HRD. While earlier research predominantly focused on the overall effectiveness of AI, the findings of this review suggest that the type of tool used, the level of human-AI interaction, and the quality of available data are decisive factors in determining actual effectiveness. This is consistent with the findings reported by Dutta and Poyil (2024), whose study examined the influence of AI adoption on organisational learning and development and similarly concluded that AI has strong potential to support HRD processes.

One of the main contributions of this review is the development of an evidence-based functional taxonomy of AI applications in learning and human resource development. Unlike technology-oriented classifications, this framework highlights the educational and organizational functions of AI tools, thereby providing researchers and practitioners with a practical perspective for selecting and implementing AI-supported learning solutions.

Despite the numerous opportunities presented by AI tools, many of the identified systems remain in the early stages of development, and insufficient longitudinal evidence is available to evaluate their long-term impact. These limitations point to important directions for future research, including assessing the sustained effects of AI tools, examining ethical and cultural considerations, and evaluating their performance across different organisational contexts. One of the central implications of this review is that AI in professional learning and development remains at a formative stage. Although AI cannot fully replace human-led development and training functions, it can make HRD processes more intelligent and contribute to the creation of more sustainable and effective learning organisations (Dutta & Poyil, 2024).

Although this review generated valuable insights into AI tools for HRD, several limitations should be acknowledged. First, the quality and accuracy of the findings depend heavily on the methodological rigour of the included studies; limitations such as small sample sizes or incomplete analyses may have influenced the results. Second, the rapid evolution of AI may render certain tools or findings obsolete within a relatively short period. Third, limited access to some databases and the lack of indexing for certain relevant studies may have resulted in the exclusion of valuable evidence.

Future research should consider conducting economic analyses and cost–benefit evaluations of AI-assisted systems in comparison with traditional professional development approaches. Researchers may also focus on developing theoretical and practical frameworks that integrate AI with contemporary learning approaches, such as blended learning and mobile learning, in order to establish more comprehensive organisational learning models. From an implementation perspective, enhancing AI literacy among managers and employees through specialised training is essential for effective adoption. Organisations should also establish interdisciplinary teams consisting of AI specialists, instructional designers, and HRD professionals to develop personalised and adaptive learning systems, as recommended by Copur-Gencturk et al. (2024). Such interdisciplinary collaboration can improve the identification of key learning concepts and increase the impact of AI in learning environments.

Finally, organisations must prioritise the development of ethical and security policies to safeguard employee data and foster cultures rooted in trust and confidentiality (Demszky et al., 2023). Strengthening these foundations will help promote employee motivation and engagement in professional development initiatives.

Overall, this review demonstrates that AI applications are becoming increasingly integrated into learning and professional development across a variety of educational and organizational settings. The proposed functional taxonomy provides a structured framework for understanding these applications and may support future research and practice. Nevertheless, the current evidence base remains relatively limited in terms of geographical diversity, organizational HRD contexts, and longitudinal evaluation. Consequently, while AI represents a promising direction for learning and HRD, additional high-quality empirical research is required to better understand its long-term effectiveness and broader organizational impact.

Although this systematic review was conducted rigorously, it is subject to several limitations. First, although the three selected databases are comprehensive and internationally recognized, only studies published in English were included. Consequently, relevant evidence reported in other languages may have been overlooked. Similarly, studies published outside peer-reviewed journals or other reputable publication outlets were excluded. Future reviews could broaden the evidence base by incorporating additional databases, grey literature, and studies published in multiple languages.

Second, despite employing a comprehensive search strategy, some relevant studies may not have been retrieved because they used discipline-specific terminology without explicitly referring to artificial intelligence. Therefore, the possibility of selection bias cannot be entirely excluded.

Future systematic reviews may also benefit from focusing specifically on organizational human resource development contexts as the body of evidence continues to expand, allowing for more context-specific conclusions regarding AI adoption and its implications for workplace learning.

Despite these limitations, this review provides a comprehensive synthesis of the current evidence and develops a function-oriented taxonomy that complements existing technology-based classifications by emphasizing the educational and organizational functions of AI applications. The proposed framework offers a conceptual foundation for future empirical research and may assist researchers and practitioners in aligning AI technologies with learning and human resource development objectives.

Declaration of Competing Interest

The author declares that he has no competing financial interests or known personal relationships that would influence the report presented in this article.

References

Ardichvili, A., Dirani, K., Jabarkhail, S., El Mansour, W., & Aboulhosn, S. (2024). Using generative AI in human resource development: an applied research study. *Human Resource Development International*, *27(3)*, 388–409. https://doi.org/10.1080/13678868.2024.2337964

Arulsamy, A., Singh, I., Kumar, S., Jetal, J., Panchal, J., & Bajaj, M. (2023). Employee Training and Development Enhancing Employee Performance -A Study. *16*. 406.

Barthakur, A., Joksimovic, S., Kovanovic, V., Mello, R. F., Taylor, M., Richey, M., & Pardo, A. (2022). Understanding Depth of Reflective Writing in Workplace Learning Assessments Using Machine Learning Classification. *IEEE Transactions on Learning Technologies, 15(5)*, 567–578. https://doi.org/10.1109/TLT.2022.3162546

Bhatt, P., & Muduli, A. (2023). Artificial intelligence in learning and development: a systematic literature review. *European Journal of Training and Development*. *47(7-8)*, 677-694. https://doi.org/10.1108/EJTD-09-2021-0143

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, Ph., Chong, S., & Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: a call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education*, *21*, 4. https://doi.org/10.1186/s41239-023-00436-z

Burstein, J., Shore, J., Sabatini, J., Moulder, B., Holtzman, S., & Pedersen, T. (2012). The Language MuseSM System: linguistically focused instructional authoring. *ETS Research Report Series, 2012(2)*, i–36. https://doi.org/10.1002/j.2333-8504.2012.tb02303.x

Burstein, J., Shore, J., Sabatini, J., Moulder, B., Lentini, J., Biggers, K., & Holtzman, S. (2014). From teacher professional development to the classroom: how NLP technology can enhance teachers' linguistic awareness to support curriculum development for English language learners. *Journal of Educational Computing Research*, *51(1)*, 119–144. https://doi.org/10.2190/EC.51.1.f

Bywater, J. P., Chiu, J. L., Hong, J., & Sankaranarayanan, V. (2019). The Teacher Responding Tool: Scaffolding the teacher practice of responding to student ideas in mathematics classrooms. *Computers and Education*, *139*, 16–30. https://doi.org/10.1016/j.compedu.2019.05.004

Chang, C. C., & Hwang, G. J. (2024). ChatGPT-facilitated professional development: evidence from professional trainers' learning achievements, self-worth, and self-confidence. *Interactive Learning Environments*. *33(1)*. https://doi.org/10.1080/10494820.2024.2362798

Chng, Lay Kee. (2023). How AI Makes its Mark on Instructional design. *Asian Journal of Distance Education, 18(2)*, 32-41. https://doi.org/10.5281/zenodo.8188576

Cohen, B., DuBois, S., Lynch, P. A., Swami, N., Noftle, K., & Arensberg, M. B. (2023). Use of an Artificial Intelligence-Driven Digital Platform for Reflective Learning to Support Continuing Medical and Professional Education and Opportunities for Interprofessional Education and Equitable Access. *Education Sciences*, *13(8)*, 760. https://doi.org/10.3390/educsci13080760

Copur-Gencturk, Y., Li, J., & Atabas, S. (2024). Improving Teaching at Scale: Can AI Be Incorporated into Professional Development to Create Interactive, Personalized Learning for Teachers? *American Educational Research Journal*. *61(4)*. https://doi.org/10.3102/00028312241248514

Copur-Gencturk, Y., Li, J., Cohen, A. S., & Orrill, C. H. (2024). The impact of an interactive, personalized computer-based teacher professional development program on student performance: A randomized controlled trial. *Computers and Education*, *210*, . https://doi.org/10.1016/j.compedu.2023.104963

Demszky, D., Liu, J., Hill, H. C., Jurafsky, D., & Piech, C. (2023). Can Automated Feedback Improve Teachers' Uptake of Student Ideas? Evidence From a Randomized Controlled Trial in a Large-Scale Online Course. *Educational Evaluation and Policy Analysis. 46(3)*, 483-505. https://doi.org/10.3102/01623737231169270

Dutta, D., & Poyil, A. K. (2024). The machine/human agentic impact on practices in learning and development: a study across MSME, NGO and MNC organizations. *Personnel Review*, *53(3),* 791–815. https://doi.org/10.1108/PR-09-2022-0658

Escolar-Jimenez, C. C., Matsuzaki, K., Okada, K., & Gustilo, R. C. (2019). Enhancing organizational performance through employee training and development using k-means cluster analysis. *International Journal of Advanced Trends in Computer Science and Engineering*, *8(4),* 1576–1582. https://doi.org/10.30534/ijatcse/2019/82842019

Fakhar, H., Lamrabet, M., Echantoufi, N., El Khattabi, K., & Ajana, L. (2024). Towards a New Artificial Intelligence-based Framework for Teachers' Online Continuous Professional Development Programs: Systematic Review. *International Journal of Advanced Computer Science and Applications. 15*(4). 480-493. https://doi.org/10.14569/IJACSA.2024.0150450

Grainger, M. J., Bolam, F. C., Stewart, G. B., & Nilsen, E. B. (2020). Evidence synthesis for tackling research waste. *Nature Ecology & Evolution*, *4(4),* 495–497. https://doi.org/10.1038/s41559-020-1141-6

Haddaway, N., Page, M., Pritchard, C., & McGuinness, L. (2022). PRISMA2020: An R package and Shiny app for producing PRISMA 2020- compliant flow diagrams, with interactivity for optimised digital transparency and Open Synthesis. *Campbell Systematic Reviews*. *18(2), e1230.* https://doi.org/10.1002/cl2.1230

Huang, L. Y., Dias, L., Nelson, E., Liang, L. R., Lajoie, S. P., & Poitras, E. G. (2022). The Role of Self-Improving Tutoring Systems in Fostering Pre-Service Teacher Self-Regulated Learning. *Frontiers in Artificial Intelligence*, *4*. https://doi.org/10.3389/frai.2021.769455

Kambur, E., & Akar, C. (2022). Human resource developments with the touch of artificial intelligence: a scale development study. *International Journal of Manpower*, *43(1)*, 168–205. https://doi.org/10.1108/IJM-04-2021-0216

Li, T., Ji, Y., & Zhan, Z. (2024). Expert or machine? Comparing the effect of pairing student teacher with in-service teacher and ChatGPT on their critical thinking, learning performance, and cognitive load in an integrated-STEM course. *Asia Pacific Journal of Education*, *44(1)*, 45–60. https://doi.org/10.1080/02188791.2024.2305163

Lu, J., Zheng, R., Gong, Z., & Xu, H. (2024). Supporting Teachers' Professional Development with Generative AI: The Effects on Higher Order Thinking and Self-Efficacy. *IEEE Transactions on Learning Technologies*, *17*, 1279–1289. https://doi.org/10.1109/TLT.2024.3369690

Malik, A., Budhwar, P., Patel, Ch., & Srikanth, N. (2020). May the bots be with you! Delivering HR cost-effectiveness and individualised employee experiences in an MNE. *The International Journal of Human Resource Management*. *33*. 1148-1178. https://doi.org/10.1080/09585192.2020.1859582

Martin, F., Zhuang, M., & Schaefer, D. (2024). Systematic review of research on artificial intelligence in K-12 education (2017-2022*). Computers and Education: Artificial Intelligence*, *6*, Article 100195. https://doi.org/10.1016/j.caeai.2023.100195

Mientus, L., Wulff, P., Nowak, A., & Borowski, A. (2023). Fast-and-frugal means to assess reflection-related reasoning processes in teacher training-Development and evaluation of a scalable machine learning-based metric. *Zeitschrift Fur Erziehungswissenschaft*, *26(3),* 677–702. https://doi.org/10.1007/s11618-023-01166-8

Morozevich, E. S., Korotkikh, V. S., & Kuznetsova, Y. A. (2022). The development of a model for a personalized learning path using machine learning methods. *Biznes Informatika-Business Informatics*, *16(2),* 21–35. https://doi.org/10.17323/2587-814X.2022.2.21.35

Phillips, T. M., Saleh, A., & Ozogul, G. (2023). An AI toolkit to support teacher reflection. *International Journal of Artificial Intelligence in Education*, *33(3),* 635–658. https://doi.org/10.1007/s40593-022-00295-1

Sandra, L., Lumbangaol, F., & Matsuo, T. (2021). Machine Learning Algorithm to Predict Student's Performance: A Systematic Literature Review. *TEM Journal.* 10. 1919-1927. https://doi.org/10.18421/TEM104-56

Shi, Y. N., & Guo, F. C. (2022). Exploring Useful Teacher Roles for Sustainable Online Teaching in Higher Education Based on Machine Learning. *Sustainability, 14(21).* https://doi.org/10.3390/su142114006

Siontis, K. C., & Ioannidis, J. P. A. (2018). Replication, duplication, and waste in a quarter million systematic reviews and meta-analyses. *Circulation Cardiovascular Quality and Outcomes, 11(12)*, e005212. https://doi.org/10.1161/CIRCOUTCOMES.118.005212

Stone, D. L., Deadrick, D. L., Lukaszewski, K. M. & Johnson, R. (2015), The influence of technology on the future of human resource management, *Human Resource Management Review*, *25 (2)*, 216-231. https://doi.org/10.1016/j.hrmr.2015.01.002

Votto, A., Valecha, R., Najafirad, P., & Rao, R. (2021). Artificial intelligence in tactical human resource management: A systematic literature review. International Journal of Information Management Data Insights, *1(2)*, Article 100047. https://doi.org/10.1016/j.jjimei.2021.100047

Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z. (2024). Artificial intelligence in education: A systematic literature review. *Expert Systems with Applications*, *252*(Pt. A), Article 124167. https://doi.org/10.1016/j.eswa.2024.124167

Wu, D. L., Chen, J., Deng, W., Wei, Y. T., Luo, H., & Wei, Y. Y. (2020). The Recognition of Teacher Behavior Based on Multimodal Information Fusion. *Mathematical Problems in Engineering, 2020,* Article 8269683. https://doi.org/10.1155/2020/8269683

Wulff, P., Buschhüter, D., Westphal, A., Nowak, A., Becker, L., Robalino, H., Stede, M., & Borowski, A. (2021). Computer-Based Classification of Preservice Physics Teachers' Written Reflections. *Journal Of Science Education and Technology, 30(1)*, 1–15. https://doi.org/10.1007/s10956-020-09865-1

Zawacki-Richter, O., Marín, V.I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education, 16*, 39. https://doi.org/10.1186/s41239-019-0171-0

Zhai, X., C, X., Chai, C., Jong, M., Istenic, A., Spector, J., Liu, J., Yuan, J., & Li, Y. (2021). A Review of Artificial Intelligence (AI) in Education from 2010 to 2020. *Complexity, 2021, Article 8812542*. https://doi.org/10.1155/2021/8812542