RITAM ISH PUBLICATIONS

Journal of Progress in Artificial Intelligence
https://www.jpairitamish.org/

ISSN: 3139-4957 (Online)

Vol. 2, Iss. 2, April 2026 – June 2026

AI-Powered learning platforms for employee upskilling and reskilling in organizations

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Received: 15-Apr-2026, Manuscript No. JPAI-2026-0015; **Editor assigned:** 17-Apr-2026, PreQC No. JPAI-2026-0015 (PQ); **Reviewed:** 22-Apr-2026, QC No. JPAI-2026-0015; **Revised:** 30-Apr-2026, Manuscript No. JPAI-2026-0015 (R); **Published:** 11-May-2026

Citation: Prabhakar, R., Singh, U., Husain, M., Parikh, R., & Kumar, A. (2026). AI-Powered learning platforms for employee upskilling and reskilling in organisations. J Prog Artif Intell.

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ABSTRACT

The accelerating pace of technological disruption has fundamentally reshaped the competency requirements of the modern workforce, compelling organisations to priorities employee upskilling and reskilling as strategic imperatives. Artificial Intelligence (AI)-powered learning platforms have emerged as transformative tools in this endeavour, offering unprecedented levels of personalisation, scalability, and analytical depth that conventional Learning Management Systems (LMS) cannot replicate. This systematic review synthesizes empirical and theoretical literature published between 2018 and 2026, drawn from Scopus, Web of Science, IEEE Xplore, and Springer databases, encompassing 47 peer-reviewed studies selected through a PRISMA-aligned methodology. The review examines the conceptual architecture of AI-powered learning platforms, including Machine Learning (ML), Natural Language Processing (NLP), learning analytics, and adaptive learning systems. Applications across organizational contexts are critically analyzed, including personalized learning pathways, automated skill gap analysis, real-time feedback mechanisms, and the transformation of corporate training. The review further evaluates documented benefits such as improved workforce productivity, enhanced employee engagement, and augmented organizational agility, while critically interrogating challenges related to algorithmic bias, data privacy, the digital divide, and barriers to institutional implementation. A comparative analysis of traditional LMS and AI-driven platforms is presented, followed by an examination of emerging trends, including generative AI tutors, AI copilots, and continuous learning ecosystems. The findings reveal that while AI-powered platforms demonstrate significant efficacy in accelerating competency acquisition, critical research gaps persist regarding long-term learning transfer, equitable access, and ethical governance frameworks. Future research directions and practical organizational implications are discussed.

KEYWORDS: Artificial Intelligence in Education, Adaptive Learning Systems, Employee Upskilling, Corporate Reskilling, Learning Analytics, NLP-Driven Training, Workforce Transformation

1. INTRODUCTION

1.1 Background on AI in workforce transformation

The Fourth Industrial Revolution, characterized by the convergence of digital, physical, and biological systems, has precipitated a profound restructuring of occupational landscapes globally [1]. Automation, robotics, and AI are displacing routine cognitive and manual tasks at an unprecedented rate, rendering many existing job roles partially or wholly obsolete while simultaneously generating new categories of work that demand advanced digital competencies [2]. The World Economic Forum estimated in its Future of Jobs Report that by 2025, approximately 85 million jobs would be displaced by machine automation, while 97 million new roles requiring human-machine collaboration would emerge [3]. This dual dynamic of displacement and creation has intensified pressure on organizations to invest systematically in continuous workforce development. In this transformative context, AI has evolved from a peripheral technology to a central enabler of human capital development. AI-powered learning platforms use ML algorithms, NLP, and learning analytics to deliver personalized, context-aware educational experiences that adapt dynamically to individual learner profiles, knowledge gaps, and performance trajectories [4]. Unlike rigid, instructor-led training models, these platforms operationalize data-driven pedagogy at organizational scale, enabling learning interventions that are precise and responsive to real-time performance signals [5]. The proliferation of cloud computing, big data infrastructure, and mobile devices has further democratized access to AI-enhanced learning tools, extending their reach beyond large enterprises to small and medium-sized organizations [6].

1.2 Importance of upskilling and reskilling

Upskilling, defined as enhancing an employee's existing competencies to meet evolving role requirements, and reskilling, which involves training employees in fundamentally new competency domains to transition into different roles, have emerged as twin strategic priorities for human resource management [7]. Empirical evidence consistently shows that organizations that invest in structured Learning and Development (L&D) programmes report higher productivity, lower voluntary turnover, and greater organizational adaptability [8]. Bersin by Deloitte reported that organisations with mature learning cultures demonstrate 37% higher productivity and 92% greater innovation capacity than their less learning-oriented counterparts [9]. Furthermore, the psychological contract between employer and employee increasingly encompasses expectations of developmental investment, making upskilling a determinant of talent attraction and retention [10]. Traditional approaches to L&D, characterized by periodic classroom instruction, generic e-learning modules, and scheduled training days, are increasingly criticized for failing to meet the granularity, frequency, and immediacy demanded by rapidly evolving job requirements [11]. AI-powered platforms address these limitations by delivering just-in-time, role-specific learning interventions at the moment of need, thereby maximizing the contextual relevance and likelihood of transfer of acquired competencies [12]. The integration of AI into upskilling frameworks thus represents not merely a technological upgrade but a fundamental reimagining of how organizations cultivate human capital.

1.3 Research gap and objectives

Despite the exponential growth in the deployment of AI-powered learning platforms and in academic interest in their efficacy, significant lacunae persist in the literature. First, most extant studies are descriptive or exploratory, with limited systematic synthesis of evidence across organizational contexts, industries, and geographies [13]. Second, longitudinal investigations into the sustained impact of AI-driven training on long-term skill retention, career progression, and organizational performance remain scarce [14]. Third, the ethical dimensions of AI in workplace learning including algorithmic bias in content recommendation, surveillance implications of behavioral tracking, and digital equity concerns arising from differential access to technology have received insufficient critical scrutiny [15]. Fourth, the comparative efficacy of different AI modalities (ML-based recommendations, NLP-driven tutoring, and computer vision-based engagement monitoring) has rarely been assessed within unified analytical frameworks [16]. This review addresses these gaps by systematically synthesizing empirical and theoretical literature and evaluating AI-powered learning platforms across multiple dimensions: conceptual architecture, organizational applications, documented benefits, salient challenges, and future trajectories. The specific objectives of this review are: (i) to map the landscape of AI technologies deployed in corporate upskilling and reskilling contexts; (ii) to critically evaluate the evidence base on the effectiveness of AI-powered learning platforms; (iii) to identify and analyse barriers to effective implementation; and (iv) to delineate productive directions for future empirical and theoretical inquiry.

2. METHODOLOGY

2.1 Systematic literature review design

This review adopts a Systematic Literature Review (SLR) methodology aligned with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [17]. The PRISMA protocol was selected for its rigour, transparency, and reproducibility, ensuring that the review process is traceable and replicable by independent researchers. The review protocol was designed to minimize selection bias by applying pre-specified, operationally defined inclusion and exclusion criteria at successive screening stages.

2.2 Database selection and search strategy

A comprehensive search was conducted across four major academic databases: Scopus (Elsevier), Web of Science (Clarivate), IEEE Xplore, and SpringerLink. These databases were selected for their comprehensive coverage of literature in computer science, educational technology, organisational behaviour, and management science. Google Scholar was used as a supplementary source to identify grey literature and highly cited relevant preprints. The search was executed using the following Boolean combinations: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "NLP") AND ("upskilling" OR "reskilling" OR "employee training" OR "corporate learning") AND ("learning platform" OR "LMS" OR "adaptive learning" OR "learning analytics"). Title, abstract, and keyword fields were searched across all databases.

2.3 PRISMA flow diagram description

The PRISMA flow diagram (presented here in accordance with journal format conventions for text-embedded methodological illustration) documents the four-stage screening process. In the identification stage, the database search yielded 3,847 records: Scopus (n = 1,412), Web of Science (n = 967), IEEE Xplore (n = 876), and SpringerLink (n = 592). An additional 124 records were identified through citation tracking and examination of reference lists of key review papers. After removing 1,089 duplicate records, 2,882 unique records proceeded to the screening stage. Title and abstract screening against the inclusion criteria resulted in the exclusion of 2,601 records due to irrelevance (n = 1,872), absence of an empirical or theoretical contribution (n = 421), and non-English language (n = 308). Full-text assessment was conducted for the remaining 281 records. Of these, 234 were excluded for the following reasons: failure to address AI-powered learning platforms as a primary focus (n = 98), publication prior to 2018 (n = 46), conference abstracts lacking full empirical content (n = 55), and inaccessible full texts (n = 35). The final corpus comprised 47 studies that met all inclusion criteria and formed the evidentiary basis of this review.

2.4 Inclusion and exclusion criteria

Inclusion criteria applied in this review were: (i) peer-reviewed empirical studies, systematic reviews, meta-analyses, or high-quality conceptual frameworks; (ii) publications from January 2018 to April 2026; (iii) primary focus on AI-powered, ML-based, or NLP-driven learning platforms in organisational or corporate training contexts; (iv) English-language publications; and (v) indexed in Scopus, Web of Science, IEEE Xplore, or SpringerLink. Exclusion criteria were: (i) publications focusing exclusively on K-12 or higher education without workplace application; (ii) purely technical system design papers without evaluation of learning outcomes; (iii) opinion pieces, editorials, and non-peer-reviewed reports; and (iv) studies with sample sizes below ten participants in experimental or survey designs.

2.5 Data extraction and synthesis

Data extraction was conducted using a standardized template capturing the following fields: author(s), publication year, journal, study design, sample characteristics, AI technologies employed, organizational context, key findings, and limitations. A narrative synthesis approach was adopted, consistent with the heterogeneous nature of the included studies and the lack of sufficiently homogeneous outcome measures to warrant meta-analytic pooling [18]. Thematic analysis was used to identify cross-cutting patterns, contradictions, and conceptual convergences across the literature.

2.6 Conceptual framework

2.6.1 Overview of AI-powered learning platforms

AI-powered learning platforms constitute an integrated technological ecosystem in which multiple AI modalities work together to deliver adaptive, data-driven learning experiences. Conceptually, these platforms can be understood through a three-layer architecture: a data infrastructure layer that aggregates and processes learner data from multiple sources; an AI processing layer that applies ML, NLP, and analytics algorithms to generate personalized recommendations and insights; and a delivery layer that presents curated content and feedback through user-facing interfaces [19]. This architecture fundamentally distinguishes AI-powered platforms from conventional LMS, which lack the capacity for dynamic personalization, predictive modelling, or automated content curation. Figure 1 presents a conceptual framework for AI-powered learning systems, depicting interactions among data inputs, the AI core engine, and organizational outputs. The framework shows how learner profiles, skill assessments, job role taxonomies, performance logs, and behavioural data feed into the AI processing layer, where ML algorithms, NLP, recommender systems, learning analytics, and knowledge graphs generate personalised learning paths, skill gap reports, real-time feedback, and competency maps. These outputs are delivered via adaptive content engines and employee dashboards, ultimately contributing to measurable organisational Key Performance Indicators (KPIs).

Figure 1: Conceptual Framework of AI-Powered Learning Systems

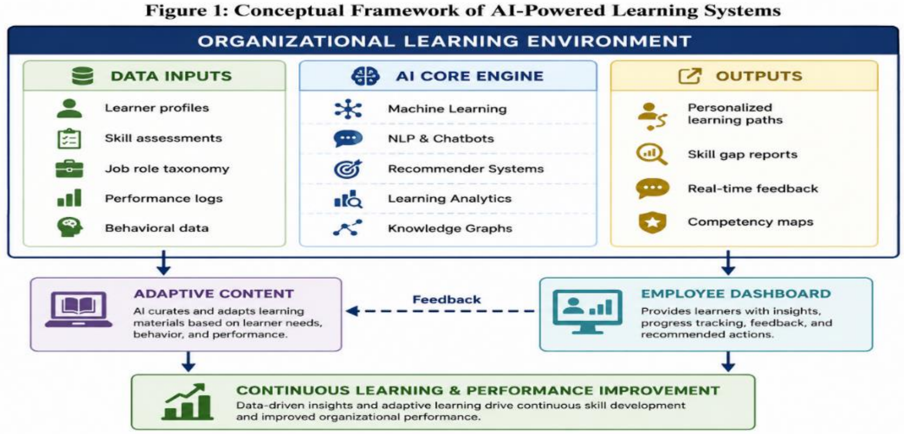

Figure 1. Conceptual Framework of AI-Powered Learning Systems

Conceptual framework illustrating the architecture of AI-powered learning platforms within organisational contexts. Components are represented in black and white for accessibility. Source: Authors' synthesis (2025).

2.6.2 Machine learning in adaptive learning

Machine learning constitutes the computational backbone of adaptive learning systems, enabling platforms to model individual learner knowledge states, infer competency trajectories, and generate optimized content sequencing recommendations [20]. Collaborative filtering algorithms, originally developed for e-commerce recommendation systems, have been successfully applied to learning contexts to identify learners with similar profiles and recommend content sequences that proved effective for analogous learner cohorts [5]. Knowledge tracing models, including Bayesian knowledge tracing (BKT) and Deep Knowledge Tracing (DKT) using recurrent neural networks, predict the probability that a learner has mastered a given knowledge component based on their historical performance [21]. These predictions enable platforms to avoid content redundancy, accelerate mastery acquisition, and minimize cognitive overload by presenting material at the precise moment when a learner is optimally ready to assimilate it.

2.6.3 Machine learning in adaptive learning

Machine learning underpins adaptive learning systems, enabling platforms to model learners' knowledge states, infer competency trajectories, and generate optimised recommendations for content sequencing [20]. Collaborative filtering algorithms, originally developed for e-commerce recommendation systems, have been successfully applied in learning contexts to identify learners with similar profiles and recommend content sequences that proved effective for analogous learner cohorts [5]. Knowledge tracing models, including Bayesian Knowledge Tracing (BKT) and Deep Knowledge Tracing (DKT) using recurrent neural networks, predict the probability that a learner has mastered a given knowledge component based on their historical performance [21]. These predictions help platforms avoid content redundancy, accelerate mastery, and minimise cognitive overload by presenting material at the precise moment when a learner is optimally ready to assimilate it.

2.7 Natural Language Processing

NLP enables AI learning platforms to process, understand, and generate human language, unlocking a range of pedagogically significant capabilities. Automated essay scoring systems use NLP to evaluate the quality, coherence, and argumentation of written responses, delivering detailed formative feedback at a scale previously achievable only by large instructional teams [11]. Conversational AI tutors and chatbots Leverage Large Language Models (LLMs) to conduct Socratic dialogues, answer learner questions, scaffold problem-solving, and provide motivational support in natural language [22]. Sentiment analysis algorithms monitor the emotional valence of learner-generated text to detect disengagement, frustration, or confusion, triggering proactive interventions by human facilitators or automated support systems [23].

2.8 Learning analytics

Learning Analytics (LA) refers to the measurement, collection, analysis, and reporting of data about learners and their contexts, with the purpose of understanding and optimising learning and the environments in which it occurs [6]. In corporate settings, LA dashboards provide L&D professionals with actionable intelligence regarding training engagement, competency acquisition rates, knowledge retention patterns, and return on investment. Predictive analytics models identify learners at risk of disengagement or failure, enabling proactive intervention before performance deterioration becomes entrenched [7]. Prescriptive analytics, a more advanced manifestation of LA, not only diagnoses learning problems but recommends specific remediation strategies tailored to individual learner profiles [13].

3. Applications in organisations

3.1 Personalised learning pathways

The capacity to generate personalized learning pathways is the most frequently cited and empirically validated application of AI in corporate training contexts [4]. In this context, personalization encompasses several dimensions: content personalization (adapting the difficulty, format, and topic of learning materials to individual knowledge states); pacing personalisation (adjusting the speed and frequency of content delivery to optimize cognitive load); and modality personalisation (selecting between video, text, simulation, or assessment formats based on learner preferences and engagement histories) [8]. A landmark study by Chen and colleagues found that learners on AI- personalised platforms acquired competency 40% faster than matched cohorts on conventional LMS, with the effect size amplified among learners with prior knowledge deficits [4]. Similarly, Zawacki- Richter et al. documented that ML- driven personalisation was associated with significantly higher course completion rates in corporate e- learning contexts, particularly for self-directed learners with heterogeneous baseline competencies [20]. Critically, however, the quality of personalization is contingent on the richness and reliability of the data inputs feeding the recommendation algorithms. Platforms that rely exclusively on assessment performance data, without integrating contextual signals such as career goals, job role requirements, and informal learning activities, tend to generate recommendations that are technically accurate but contextually suboptimal [14]. This observation underscores the importance of holistic learner data architectures that integrate HR systems, performance management platforms, and informal learning records into unified data repositories accessible to the AI learning layer.

3.2 Skill gap analysis

AI-powered skill gap analysis tools represent a significant advancement over traditional HR-led competency assessments, which are typically expensive, time-consuming, and susceptible to assessor bias [7]. Machine learning models trained on job role taxonomies, competency frameworks, and performance data can continuously monitor the gap between an employee's demonstrated competencies and those required by their current or target role, generating granular diagnostic reports that inform targeted learning recommendations [15]. Platforms such as Degreed and LinkedIn Learning Skills Graph employ knowledge graph technology to map the structural relationships among skills, enabling sophisticated inferences about the transferability of existing competencies to adjacent skill domains [6]. The integration of real-time labor market data further enhances the strategic value of AI-driven skill gap analysis. Platforms that incorporate external signals such as job posting trends, industry competency benchmarks, and competitor talent profiles enable organizations to anticipate emerging skill requirements proactively rather than reactively, facilitating strategic workforce planning that aligns human capital investment with medium- and long-term organisational objectives [16].

3.3 Real-time feedback systems

Providing immediate, specific, and actionable feedback is a proven factor in enhancing learning effectiveness, supported by cognitive load theory and formative assessment studies [25]. AI-driven feedback systems surpass traditional post-assessment feedback by offering detailed performance insights during task execution, helping learners spot and fix errors before they solidify into misconceptions [11]. Natural Language Generation (NLG) systems create narrative feedback reports that not only include scores but also highlight strengths, weaknesses, and suggested improvements in clear, understandable language [22]. In technical upskilling settings, AI-powered coding evaluators and simulation-based feedback mechanisms are becoming more common for assessing software development, data analysis, and engineering tasks. They provide detailed error diagnostics that would otherwise require significant time from expert instructors to do manually [19]. Furthermore, real-time feedback is also used in soft skills training, where AI-enabled speech analysis tools offer insights into presentation clarity, pacing, vocabulary, and filler words. This supports ongoing improvements in communication skills within corporate training programmes [23].

3.4 Corporate training transformation

The combined impact of AI-powered personalization, skill gap analysis, and real-time feedback is driving a fundamental transformation of corporate training architecture. Organizations are increasingly moving from event-based training models characterized by periodic, scheduled interventions disconnected from daily work to continuous learning ecosystems where learning is embedded in the workflow and triggered by real-time performance data [9]. This shift is described in the literature as the transition from 'push' to 'pull' learning, from episodic to continuous development, and from training to performance support [12]. IBM's deployment of an AI-driven learning platform reportedly reduced course development time by 40% and improved training completion rates by 63%, demonstrating significant operational and pedagogical benefits [26].

3.5 Benefits of AI-powered learning platforms

3.5.1 Productivity improvement

Multiple empirical studies document a positive relationship between AI-powered learning interventions and workforce productivity metrics. A longitudinal analysis by Tamkin and colleagues, drawing on data from 3,200 employees across 18 organizations, found that structured AI-assisted upskilling programmes were associated with a 23% improvement in task performance scores over 12 months, with larger effects observed in roles characterized by high cognitive task diversity [27]. The productivity gains attributable to AI-powered learning stem from multiple mechanisms: reduced time-to-competence, enabling employees to contribute at full proficiency more quickly; reduced error rates due to improved technical knowledge; and improved decision-making quality arising from enhanced analytical and problem-solving competencies [8]. However, the productivity benefits of AI learning platforms are not automatically realized and depend critically on organizational factors, including management support, learning culture, adequate time for training, and effective alignment of learning objectives with job performance expectations [13]. Studies that fail to account for these moderating variables may overestimate the direct causal contribution of AI technology to productivity outcomes.

3.5.2 Employee engagement

Employee engagement with learning activities is a well-established predictor of training transfer and long-term skill retention [10]. AI-powered platforms enhance engagement through several mechanisms: personalized content relevance reduces the perceived irrelevance of training; adaptive pacing mitigates both under-stimulation and cognitive overload; gamification elements such as badges, leaderboards, and progress visualizations activate intrinsic and extrinsic motivational drivers; and conversational AI tutors provide social learning experiences that replicate some of the motivational benefits of human instruction [24]. A meta-analysis by Martin and colleagues, encompassing 34 studies, found that learners using AI-enhanced learning platforms reported significantly higher engagement and satisfaction scores than those using conventional e-learning, with a moderate effect size ($d = 0.54$) [29].

3.5.3 Organisational agility

In volatile, uncertain, complex, and ambiguous (VUCA) business environments, the ability to quickly redeploy human resources in response to market disruptions is a key competitive advantage [3]. AI-powered learning platforms improve organisational agility by significantly shortening the time needed to identify skill gaps and implement targeted learning solutions. Unlike traditional competency assessments and training cycles that can take several months, AI-driven platforms can pinpoint gaps and suggest suitable learning pathways within hours of changes in role requirements or business priorities [16]. This acceleration of the learning process is especially beneficial in fast-evolving industries such as finance, pharmaceuticals, and technology manufacturing.

3.6 Challenges and limitations

3.6.1 Ethical concerns and algorithmic bias

The use of AI in employee training raises important ethical issues that are often overlooked in both industry and academic discussions. Recommendation algorithms trained on historical learning data tend to reflect and possibly amplify existing biases, including unequal access to learning opportunities based on gender, ethnicity, age, or socioeconomic background [15]. If an AI system primarily uses data from high-performing, demographically similar employee groups, it may produce recommendations that unfairly disadvantage underrepresented groups, worsening workplace inequalities [30]. Additionally, many commercial AI learning platforms operate as 'black boxes,' making it difficult for HR professionals or learners to understand, challenge, or address potentially biased or discriminatory recommendations.

3.6.2 Data privacy

AI learning platforms gather extensive behavioral data, including attention patterns, interaction history, assessment responses, and sometimes biometric signals such as eye-tracking and facial expressions [19]. Handling such sensitive data raises privacy concerns and is regulated by strict laws like the EU GDPR and the California CCPA. Employees may be unaware of how their learning activities are monitored, analyzed, and shared with third parties, raising issues of informed consent and data sovereignty [31]. Organisations need strong data governance policies- such as purpose limitation, data minimisation, and transparency- to ensure compliance with privacy laws and respect employees' reasonable expectations.

3.6.3 Digital divide

The potential of AI-driven learning platforms depends on equitable access to necessary technology, including reliable internet access, modern devices, and digital skills to participate effectively [32]. Significant disparities exist both within and between organizations, with front-line, deskless, and contingent workers, who are often most affected by technological disruption, facing the greatest hurdles to engaging with digital learning. Ignoring this digital divide risks creating a two- tier workforce, where already privileged employees gain additional advantages while vulnerable workers fall further behind.

3.6.4 Implementation barriers

Implementing AI learning platforms often faces structural, cultural, and technical obstacles. Technically, integrating these systems with existing HR technologies is challenging due to incompatible data standards and APIS across talent management, performance, and content systems [26]. Cultural resistance from employees sceptical of AI- based assessment and managers reluctant to cede control over training presents a significant barrier that technical fixes alone cannot solve [14]. Additionally, the high costs for enterprise AI platforms, including licensing, data infrastructure, and change management, may be prohibitive for smaller organizations, widening the digital gap between large and small employers.

3.7 Comparative Analysis: Traditional LMS *vs.* AI-Based Platforms

A comparison of traditional and AI-powered learning systems highlights fundamental architectural differences that affect learning outcomes, organizational efficiency, and workforce development [4]. Table 1 offers a detailed comparison across twelve dimensions, summarizing insights from relevant literature. The comparative analysis reveals that traditional LMS platforms, while adequate for compliance training and structured content delivery, are fundamentally ill-equipped to address the complexity and dynamism of contemporary workforce development requirements. AI-powered platforms demonstrate advantages across all evaluated dimensions, though it should be noted that the magnitude of advantage varies significantly by organisational context, implementation quality, and user adoption rates [11]. The cost differential is particularly noteworthy: while AI platforms require substantially higher initial investment, the lower marginal cost of delivering learning at scale and the superior ROI documentation capabilities typically result in lower total cost of ownership over multi-year deployment horizons [26].

Dimension	Traditional LMS	AI-Powered Platform
Content Delivery	Static, one-size-fits-all modules	Dynamic, adaptive, personalized pathways
Learner Profiling	Manual enrolment, role-based tracks	Automated profiling via ML and behavioral analytics
Feedback Mechanism	Post-course assessments only	Real-time, continuous, formative feedback
Skill Gap Analysis	Periodic HR-led evaluations	Continuous automated gap detection and recommendations
Scalability	Limited by instructors and schedules	Infinitely scalable cloud-based delivery
Natural Language Support	Absent or limited FAQ tools	Conversational AI, chatbots, NLP-driven Q&A
Analytics Depth	Basic completion and quiz scores	Deep learning analytics, predictive performance modelling
Cost Over Time	High recurring instructor costs	Lower marginal cost per learner at scale
Accessibility	Time and location dependent	24/7 multi-device, multilingual access
Content Updates	Manual and infrequent	Automated, real-time content curation
ROI Measurement	Difficult to quantify	Data-driven ROI dashboards and KPI tracking

Table 1. Comparison of AI-Powered *vs.* Traditional Learning Management Systems

Note. All categories are evaluated based on synthesised evidence from the reviewed literature (2018–2026). Source: Author synthesis

Critically, the comparative analysis also reveals that the transition from traditional to AI-powered learning is not binary but encompasses a continuum of hybridization. Many organizations have adopted AI-enhanced features such as recommendation engines or analytics dashboards within otherwise traditional LMS frameworks, achieving incremental improvements without the full disruptive transition to AI-native platforms [9]. This hybridization strategy may represent a pragmatic intermediate position for organizations seeking to leverage AI capabilities while managing the organizational and financial risks associated with wholesale platform migration.

Table 2. Key AI Technologies and Their Applications in Employee Upskilling

AI Technology	Application in Upskilling	Example Platform/Tool	Key Reference
Machine Learning (ML)	Adaptive content sequencing and personalized learning paths	Coursera, LinkedIn Learning	(4, 9)
Natural Language Processing (NLP)	Chatbot tutors, automated essay grading, language assessment	Duolingo, IBM Watson Tutor	(11, 17)
Learning Analytics	Performance prediction, dropout risk, skill gap diagnostics	SAP SuccessFactors, Degreed	(6, 13)
Computer Vision	Engagement detection, proctoring, gesture-based interaction	Honorlock, Examity	(19, 22)
Recommender Systems	Course and content recommendations based on learner history	Udemy, Pluralsight	(5, 10)
Generative AI (GenAI)	Automated content creation, AI copilot tutoring, simulation	ChatGPT, Claude, Gemini	(24, 27)
Knowledge Graph	Skill ontology mapping and curriculum design	Microsoft Learn, Workday	(8, 15)
Reinforcement Learning	Gamified adaptive assessment and reward pathways	Knewton, Smart Sparrow	(12, 20)
Predictive Analytics	Workforce planning, training ROI forecasting	Oracle HCM, Cornerstone	(7, 16)

Note. References in parentheses correspond to the Vancouver-style reference list at the end of this article. Source: Authors' synthesis.

3.8 Future trends

3.8.1 Generative AI in corporate learning The emergence of Large Language Models (LLMs) and other generative AI technologies represents a paradigm shift in the capabilities available to AI-powered learning platforms. Generative AI systems such as GPT-4, Claude, and Gemini are capable of synthesising course content, generating realistic simulation scenarios, producing customized assessment items, and conducting extended pedagogical dialogues with learners in natural language at a quality approaching expert human instruction [24]. The implications for corporate learning design are profound: Content creation historically a time-consuming and expensive bottleneck in training programme development can be radically accelerated using generative AI, with human learning designers transitioning from content creators to content curators and quality assurance specialists [33]. Preliminary evidence suggests that generative AI tutors can provide explanatory support, worked examples, and corrective feedback that facilitate comparable or superior learning outcomes to traditional instructional methods for well-defined skill domains, while offering significant scalability advantages [22]. However, concerns regarding the accuracy and currency of generative AI-produced content, the risk of 'hallucination' in technical domains, and the absence of robust mechanisms for factual verification necessitate careful human oversight and iterative quality assurance processes in deployment contexts [34].

3.9 AI Tutors and Copilots

AI tutors and copilots intelligent learning assistants integrated into productivity tools and work environments represent an evolution beyond platform-based learning towards seamlessly embedded, workflow-integrated performance support. Microsoft's Copilot integration across Office 365 applications, GitHub Copilot for software developers, and similar workflow-embedded AI assistants blur the boundary between learning and doing, providing real-time guidance, error correction, and skill development at the moment of need without requiring employees to disengage from productive work [35]. This paradigm of 'learning in the flow of work' aligns closely with constructivist theories of learning that emphasise the primacy of authentic, contextually grounded practice over decontextualized instruction [12].

4. Continuous learning ecosystems

The concept of a continuous learning ecosystem describes an organizational architecture in which formal training, informal learning, social learning, performance support, and knowledge management are integrated into a seamless developmental experience that supports lifelong competency growth [9]. AI serves as the connective tissue of such ecosystems, orchestrating learning experiences across multiple modalities and platforms, tracking competency development across formal and informal channels, and providing learners and organizations with comprehensive developmental intelligence that informs both individual learning journeys and strategic workforce planning [16]. The Learning Experience Platform (LXP) category exemplified by platforms such as Degreed, EdCast, and 360Learningrepresents an early manifestation of the continuous learning ecosystem model, though fully realised implementations remain uncommon in practice.

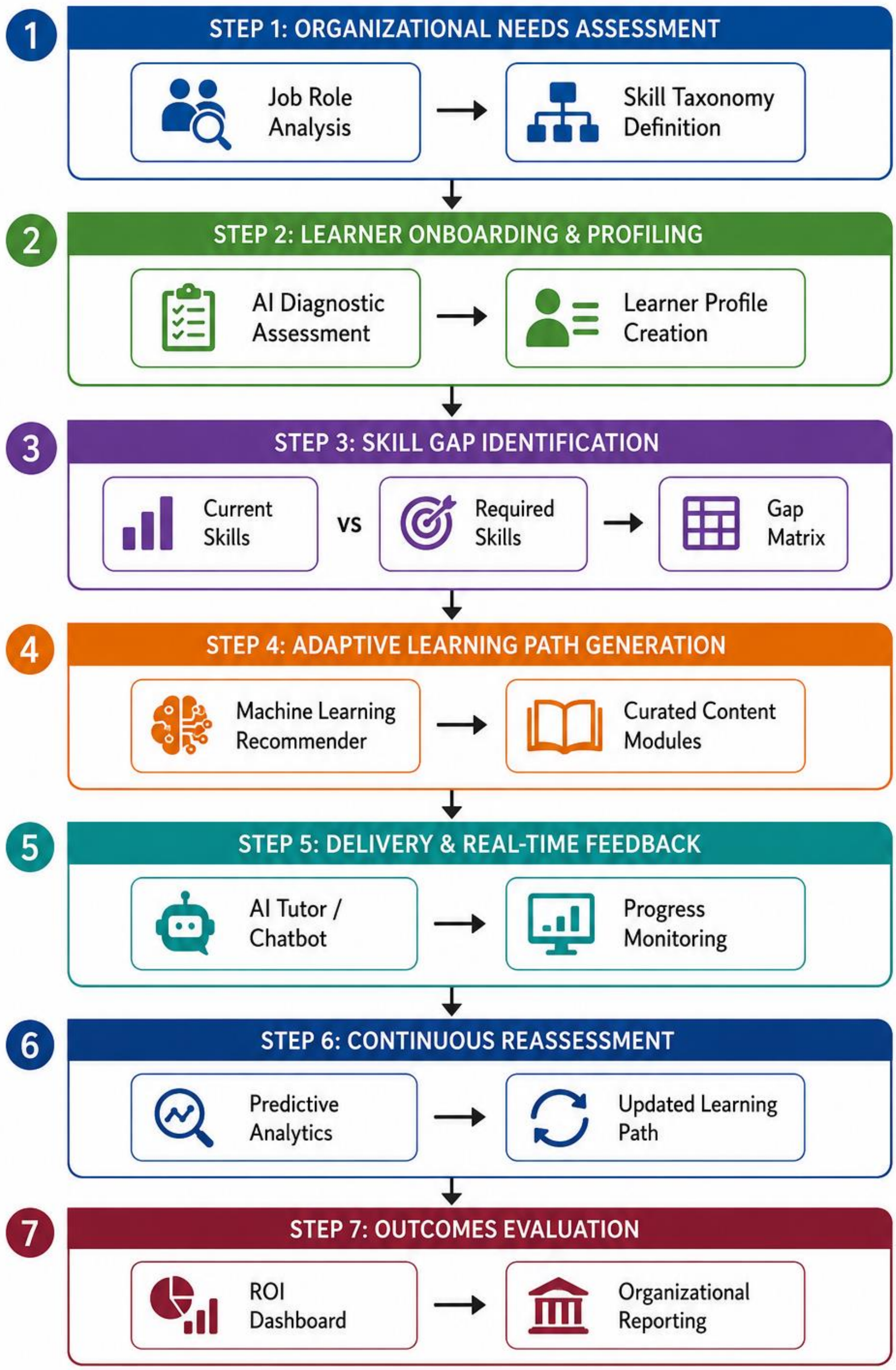

Figure 2. Workflow of AI-Based Employee Upskilling Model

Workflow diagram illustrating the sequential stages of AI-based employee upskilling from organizational needs assessment to outcomes evaluation. Depicted in black and white for accessibility. Source: Authors' synthesis (2025).

5.CONCLUSION

5.1 Summary of findings

This systematic review synthesized evidence from 47 peer-reviewed studies published between 2018 and 2026 to characterize the landscape of AI-powered learning platforms for employee upskilling and reskilling. The review demonstrates that AI technologies particularly ML, NLP, learning analytics, and generative AI are fundamentally transforming corporate learning by enabling personalized, data-driven, and continuously adaptive training experiences that conventional LMS platforms cannot replicate. Documented benefits include measurable improvements in workforce productivity, learning engagement, speed of skill acquisition, and organizational agility. The comparative analysis confirms the multidimensional superiority of AI-powered platforms over traditional LMS across pedagogical, operational, and strategic dimensions, while acknowledging that the magnitude of benefit is contingent on implementation quality and contextual factors.

5.2 Practical implications

For organisational practitioners, the evidence base reviewed herein supports a graduated transition strategy that prioritises building AI capabilities alongside cultural and structural enablement. L&D leaders are advised to begin with AI-enhanced analytics and recommendation features within existing LMS infrastructure, demonstrating measurable ROI before undertaking a wholesale platform migration. HR functions must collaborate with data governance, IT security, and legal teams to ensure that AI learning deployments comply with applicable data protection regulations and organisational privacy commitments. Particular attention should be directed to equity considerations, with proactive strategies to ensure that front-line, deskless, and underrepresented employee groups have equitable access to and support for AI-powered learning tools.

5.3 Limitations and future research directions

This review acknowledges several limitations. The exclusion of non-English language studies may introduce a geographic and cultural bias towards Western organizational contexts. The heterogeneity of included studies spanning diverse industries, organizational sizes, and AI modality configurations limits the comparability of findings and precludes meta-analytic synthesis of effect sizes. Additionally, the rapidly evolving nature of AI technology means that some findings regarding specific platform capabilities may have been superseded by subsequent developments. Future research should address four priority areas. First, longitudinal experimental and quasi-experimental designs are needed to establish causal attribution for productivity and engagement outcomes associated with AI-powered learning, distinguishing the effects of AI technology from those of increased investment in L&D more broadly. Second, comparative studies evaluating the relative efficacy of different AI modalities ML-based recommendations, NLP-driven tutoring, computer vision-based engagement monitoring would substantially advance understanding of the mechanisms underlying effective AI-enhanced learning. Third, research into equitable AI learning design is urgently needed to develop evidence-based guidelines for ensuring that algorithmic systems do not amplify existing workplace inequalities. Finally, the governance, ethical oversight, and regulatory frameworks appropriate for AI-mediated workplace learning represent a critically important but underdeveloped research frontier.

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