



**STRATEGIC RESKILLING AND UPSKILLING OF THE IT
WORKFORCE IN THE AI ERA: A SYSTEMATIC REVIEW OF
ORGANISATIONAL PRACTICES AND OUTCOMES**

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Abstract

Purpose: This study aims to systematically review and synthesise existing literature on AI-driven reskilling and upskilling of the IT workforce, focusing on organisational practices, theoretical foundations, and performance outcomes.

Methodology: A systematic literature review (SLR) was conducted using PRISMA guidelines, with studies sourced from Scopus, Web of Science, and Google Scholar between 2015 and 2025. A total of 25 relevant studies were selected and analysed using an inductive content analysis approach, supported by the Ability–Motivation–Opportunity (AMO) framework.

Findings: The results indicate that reskilling and upskilling have evolved into strategic organisational capabilities driven by AI adoption. Key findings highlight the importance of AI-enabled HR practices, continuous learning systems, and organisational support in enhancing workforce competence and performance. The study identifies five major themes, including HR strategy alignment, learning frameworks, technology-mediated learning, performance outcomes, and implementation challenges.

Theoretical Implications: The study contributes by developing an integrated AMO-based framework, supported by Human Capital Theory, Dynamic Capability Theory, and Organisational Learning Theory.

Practical Implications: The findings provide actionable insights for HR leaders, organisations, and policymakers to design effective workforce development strategies in the AI era.

Originality: This study offers a structured synthesis of fragmented literature and proposes a unified framework linking AI strategy, workforce competence, and organisational performance.

Keywords: Artificial Intelligence; Reskilling; Upskilling; Workforce Transformation; Human Resource Management

1. Introduction

The rapid innovation of artificial intelligence (AI) has radically altered the essence of work, especially in the IT workforce, as automation, data-driven decision-making, and smart systems are defining the organisational process and demand of the skillset. The use of AI technologies is gradually replacing or supplementing traditional job roles, and a transformation of digital, cognitive and adaptive competencies as a shift towards more routine technical skills is occurring (Asif et al., 2024; Ahmed, 2024). Not only technical skills have been added to employees, they are now required to have problem-solving skills, critical thinking, and the capacity to learn continuously to be relevant in AI-driven settings (Tariq, 2024; Kanagarla, 2024). This paradigm has increased the significance of workforce development plans, especially reskilling and upskilling, as organisations aim to match the capabilities of the employees to the emerging changes in technology (Asiedu and Tenakwah, 2025; Farawowan, 2025).

Reskilling and upskilling have become key solutions to the increasing gap on the ability of the current workforce with potential future jobs demand (Ekuma, 2023). Artificial intelligence has increased the rate of skill obsolete, which makes many past-traditional competencies insufficient and at the same time, inspires a variety of interdisciplinary competencies (Babashahi et al., 2024; Morandini et al., 2023). This change has caused a lot of workforce discontinuity as the employees need to evolve in line with new technologies and organisational processes. Concurrently, organisations are under more and more pressure to devise successful ways of coping with this shift to make sure that workers are productive and engaged (Elly & Lostar, 2025; Adio et al., 2025). Although there is increasing significance of this topic, the literature is still divided, with researchers tending to concentrate on specific areas including training strategies, the use of technology or how employees feel, but not present a synthesis of organisational actions and results (Egasmara et al., 2025; Hajam & John, 2024).

One of the gaps in the literature that are of critical interest is the lack of combing the dimensions of significance to the transformation of workforce. Although there are studies on HR strategies to develop the workforce, others are based on AI-driven learning platforms or an organisation performance performance, yet none of them tries to implement these factors in a coherent system (Bauer et al., 2023). This siloing restricts the capacity to know how organisations can successfully design and undertake reskilling and upskilling programs to cope with AI uptake. Specifically, one of the issues is the absence of systematic synthesis to integrate human resource strategies, technology-based learning systems, and organisational outputs, which makes it hard to determine the best work practices and strategies (Fenwick et al., 2024; Madanchian and Taherdoost, 2025). Moreover, the current literature hardly incorporates these dimensions in a unified theoretical framework, which leaves a gap in comprehending the ways the workforce development plays a role in organisational performance (Jamal & Sakka, 2025).

In this context, the research will use the framework of AbilityMotivationOpportunity (AMO) as the theoretical perspective to fill this gap (Crogman et al., 2025). The AMO framework gives a holistic view of the impact of organisational practices on employee performances through three major dimensions that are development of employee abilities, motivation to use the abilities and opportunity to use the abilities in organisational settings. Besides AMO, the paper relies on Human Capital Theory, which focuses on the significance of investing in skills to boost productivity and organisational performance (Wuttaphan, 2017), Dynamic Capability Theory, which elucidates how organisations adapt to changing environments by having continuous resource reconfigurations (Bleady et al., 2018), and Organisational Learning Theory, which elucidates the importance of continuous Combining the theories offers a multidimensional perspective on AI-powered workforce change, interconnecting the personal ability building with the organisational flexibility and performance results (Akindoyin and Akuche, 2023).

The main aim of the research is to provide a review and synthesis of the available literature on the topic of AI-driven reskilling and upskilling in an organisational setting, but with an emphasis on defining key practices and theoretical concepts and outlining organisational implications. Specifically, the study will be aimed at gaining insights into how organisations influence the way workforce is developed, as well as how organisations implement the AI-enabled learning systems to improve the acquisition of skills, and what the implications of such activities are on the performance of organisations. In this manner, this paper will attempt to develop an organized concept of workforce change in the AI age and propose a comprehensive system, which entails the combination of the HR-based policies, learning processes, and performance results.

To make the paper more logical and understandable, the paper is structured in accordance with IMRaD structure. The methodology section presents the methodology of the systematic literature review, data source, selection criteria and methods of analysis. The main results, including thematic analysis and synthesis of the selected studies are disclosed in the results part. These findings are elaborated on in the discussion section as they relate to the theoretical frameworks and implications to organisational contexts, and identify research gaps. Lastly, a conclusion part is given to summarise the main contributions made by the research and give future research directions.

2. Methodology

2.1 Research Design

The paper assumes the format of a systematic literature review (SLR) to take into consideration organisational practices as far as reskilling and upskilling of the workforce are concerned in the context of artificial intelligence (AI). The SLR approach is particularly open to synthesising fragmented and emerging research due to its ability to be used to systematically identify key themes, patterns and gaps in research. The systematic approach assists in enhancing the methodological rigour of the study, offer transparency in the choice of the study, and minimise the possible bias in the interpretation of the study findings.

2.2 Search Strategy

An extensive literature search was carried out in major academic databases, such as Scopus, Web of Science, DOAJ, and Google Scholar, to make sure the search is comprehensive and covers the high-quality research in the fields of management and technology. To ensure that the recent trends in AI-driven workforce transformation are captured, the search was limited to those studies that were published since 2015 and until 2025. A set of keywords and Boolean operators were used, including: artificial intelligence AND reskilling, artificial intelligence AND upskilling, artificial intelligence-driven HRM AND workforce development. The search strategy was to find the studies that consider the technological and organisational aspects of workforce transformation.

2.3 Inclusion and Exclusion Criteria

To ensure relevance and quality, the inclusion and exclusion criteria were clearly outlined to select the studies. It included studies that were interested in AI-driven reskilling and upskilling in an organisational or workforce context and published as peer-reviewed journal articles or other relevant conference papers. The empirical and theoretically based studies were taken into consideration, but had to be meaningful to the workforce development in the AI context. The studies were filtered out based on the following criteria: the study had to address the issue of AI-related workforce skill-building, as well as had to lack an organisational focus, to be purely technical in nature, or to overlap in concept without making any distinct contribution. In addition, the studies, which were not empirical or theoretical as far as depth is concerned, were removed. The filtering mechanism led to the final list of studies not only being relevant, but also very much in line with the objective of the study.

2.4 Screening Process (PRISMA Framework)

The process of selection of the studies was based on the PRISMA (Preferred Reporting Items in Systematic Reviews and Meta-Analyses) framework that consists of the following steps: identification, screening, eligibility, and inclusion. To begin with, 160 records were found including 150 records in academic databases and 10 other records identified through manual reference checks. Having eliminated 40 duplicate records, 120 studies were left to undergo title and abstract screening. At this point, 60 research papers were eliminated because they are irrelevant. The rest 60 studies were undergone full-text evaluation so as to determine their eligibility. At this phase, 35 studies were filtered out due to certain reasons, such as the lack of focus on AI and workforce skills (n = 10), absence of organisational context (n = 5), overlap of concepts with other studies (n = 9), and the lack of empirical or theoretical contribution (n = 11). Consequently, 25 studies were used up to the final systematic review. This increased sample enhances comprehensiveness and analytical acumen of the study. The PRISMA flow diagram as shown in figure 1 was applied in the selection process.

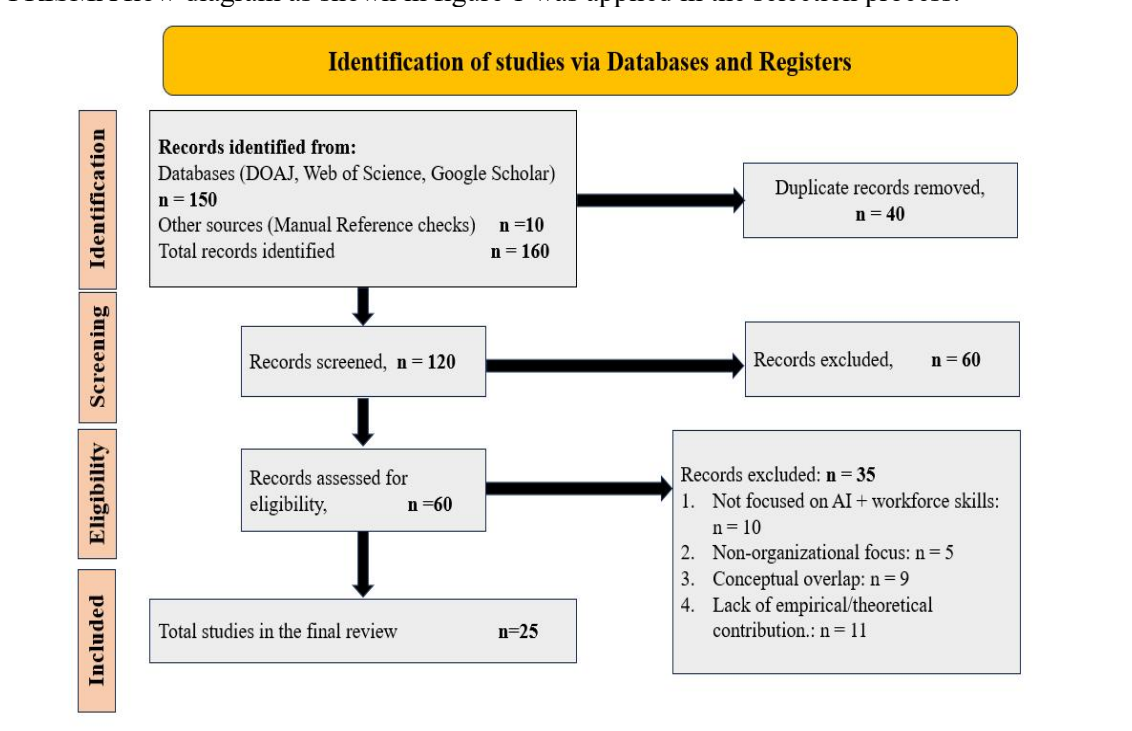


Figure 1. Study Selection Process Based on PRISMA Framework

2.5 Data Extraction

A systematic method of data extraction was employed to offer uniformity over the selected researches. All the significant information like author information, context of the research, research methodology, key variables and key findings were enlisted and systematically arranged. This has been useful to effectively compare across studies and to identify trends associated with AI driven workforce transformation and organisational practices.

2.6 Analytical Approach

A content analysis approach was adhered to, the approach followed was inductive content analysis method, which was used to analyse the selected studies. This involved determining key concepts in each of the studies to cluster similar concepts into categories, and afterwards synthesise the categories into larger themes. The inductive quality of the analysis enabled themes to come out directly on the data, and this provided a flexible but systematic framework on how the literature should be interpreted.

2.7 AMO Framework Application

The research findings were discussed within the frames of the AbilityMotivationOpportunity (AMO) concept, which provides the organised view of the effects of organisational practices on employee performance. The selected works have been discussed in terms of their contribution to enhancing the abilities of employees by training and developing their skills, motivation of employees by engaging them and rewarding them with incentive system, and the opportunity to apply the developed skills in practice with the assistance of supportive organisational structures. This model allows one to comprehend, in detail, how organisations design and implement effective reskilling and upskilling strategies in AI-based businesses and related the development of workforce capabilities with the results of organisational performance.

3. Results

3.1 Summary of Selected Studies

The final review will comprise 25 studies, which will be a reflection of a wide and interdisciplinary body of literature that will discuss AI-driven reskilling and upskilling within an organisational context. These works add cross-cutting perspectives across different arenas like corporate organisations, higher education, manufacturing, banking, SMEs and global labour markets that provides it with a overall perspective of workforce transformation in the AI age.

This has been evidenced in the fact that the evolution of the AI-driven workforce development is no longer tunnel-visioned about the improvement of the technical skills but has now evolved into a multidimensional organisational capability. The studies are putting reskilling and upskilling as the strategic response to the technological disruption and the need to align the technological adoption, human resource practices and organisational goals.

As an example, the support of the organisation and sector-specific implementation are significant as demonstrated by Hasan et al. (2024) and Khushk et al. (2026).

More so, macro-level analyses (e.g., Acemoglu and Restrepo, 2020; Autor, 2015; Kromann et al., 2020) indicate more general trends in the labour market, how automation is changing the employment structure, productivity, and wage dynamics. Meanwhile, research on the organisational level (e.g., Ramachandran et al., 2024; Mahade et al., 2025) addresses the role of AI-enabled learning systems and HR analytics in improving the competence of the workforce.

In general, the chosen articles all prove that AI-driven reskilling is a technological requirement as well as a strategic organisational need and therefore must be a concerted effort across various levels.

Table 1. Summary of Selected Studies on AI and Workforce Upskilling/Reskilling

Author(s) & Year	Context/Sample	Key Variables	Key Findings
Appiah (2024)	Global workforce	AI perception, trust, upskilling	Positive perception and trust in AI increase willingness to engage in reskilling initiatives.
Appiah (2025)	Corporations (2018–2022)	AI adoption, strategy, learning culture	Strategic alignment and learning culture enhance workforce upskilling outcomes.
Hasan et al. (2024)	250 employees, Bangladesh	Upskilling, workforce agility, organisational support	Organisational support significantly improves adaptability and performance.
Fenwick et al.	Organisations	HRM, AI adoption,	HRM aligns AI

(2024)		human-centric approach	implementation with human needs, improving adoption success.
Ramachandran et al. (2024)	Training context	AI training, personalised learning	AI enables tailored training, enhancing engagement and knowledge retention.
Khushk et al. (2026)	Chinese automotive industry	AI in HR, employee acceptance, career growth	AI improves employee acceptance, skill development, and performance.
Mahade et al. (2025)	215 participants, UAE	AI insights, HRM performance, decision-making	AI enhances HRM through improved decision-making.
Vidas-Bubanja et al. (2023)	Western Balkans	Reskilling, digital skills	Continuous reskilling is essential for digital transformation.
Mamela et al. (2020)	Banking sector, South Africa	Reskilling, AI adaptation	Workforce reskilling is necessary for AI-driven change.
Revtiuk & Pawlowska-Nowak (2025)	SMEs, 34 countries	Skills shortage, AI adoption	Skills shortages both drive AI adoption and increase demand for advanced skills.
Morandini et al. (2023)	Organisations	AI impact, skills transformation	AI significantly reshapes skills, requiring continuous upskilling and reskilling.
Ng et al. (2023)	Teachers (post-pandemic)	AI competencies, digital skills	AI competencies enhance 21st-century skills and adaptability.
Kawa (2025)	Labour market analysis	AI transformation, meta-skills	AI increases demand for adaptability, cognitive flexibility, and interdisciplinary skills .
Acemoglu & Restrepo (2020)	US labour markets	Robots, employment, wages	Automation reduces employment and wages in highly exposed regions .
Minbaeva (2021)	HRM context	Digitalisation, AI disruption	AI disrupts HRM, requiring transformation in workforce management .
Autor (2015)	Labour market (historical)	Automation, job structure	Automation replaces routine tasks but complements human skills .
Nedelkoska & Quintini (2018)	OECD countries	Automation risk, training	Automation increases need for training; skills determine job risk .
Tambe et al. (2019)	Organisations	AI in HR, data analytics	AI improves HR decisions but faces ethical and data challenges .
Graetz & Michaels (2015)	17 countries, industries	Robots, productivity	Robots increase productivity and wages but

			may reduce low-skill labour demand .
Damioli et al. (2021)	5257 firms (global)	AI patents, productivity	AI adoption positively impacts firm-level productivity .
Fossen & Sorgner (2019)	Labour market	Digitalisation, occupations	Digital technologies have both destructive and transformative effects on jobs .
Arntz et al. (2017)	OECD labour market	Automation risk	Automation risk is lower than expected due to task variability .
Bessen (2018)	Manufacturing industries	AI, demand, employment	Technology can increase employment through demand expansion .
Babina et al. (2024)	Firms (global)	AI investment, innovation	AI drives firm growth through product innovation .
Kromann et al. (2020)	Cross-country industries	Automation, productivity	Automation significantly increases productivity and wages

3.2 Thematic Findings

The reviewed literature reveals that five pertinent themes of strategic reskilling and upskilling in the age of AI are present. The themes describe how organisations are changing to meet the changing skills needs through the HR strategy, learning structures, technology mediated structures, performance based development, and barrier management.

Theme 1: AI-led Skill Renewal and Strategic HR Approaches

The results are a strong indication that skill renewal through AI has moved on to become an operational HR practice, instead of a strategic organisational practice. Organisations are making more reskilling programmes a part of larger digital change programs, with HRM in the centre of the change. Such studies as the one by Appiah (2025) and the one by Fenwick et al. (2024) prove that the following are the key enablers of a successful reskilling: leadership commitment and organisational learning culture. These results are supported by Hasan et al. (2024), who demonstrate that the organisational support mechanisms can greatly increase the agility and adaptability of the workforce. Notably, the literature indicates that reskilling is best implemented as part of long-term workforce planning, and not as a response measure. Another theme is also indicative of a movement towards human-centric AI adoption, where the HR strategies are aimed at balancing between the technological and employee efficiency, engagement, and trust.

Theme 2: Learning Frameworks and Competency Development Models

In the reviewed literature, the significance of the structured and adaptive learning frameworks in facilitating the workforce transformation is consistently noted. Such environments powered by AI necessitate not just technical competencies, but also meta-competencies such as critical thinking, problem-solving, and cognitive flexibility. According to the studies by Ng et al. (2023) and Morandini et al. (2023), the growing popularity of competency-based models that combine digital skills with behavioural and cognitive abilities is noticeable. These frameworks are defined by the ongoing learning trajectories, individualised skill development, and the alignment with organisations goals. Moreover, macro-level research (e.g., Nedelkoska and Quintini, 2018; Kawa, 2025) also shows that the requirements of skills

are changing very quickly, which proves the necessity of the lifelong learning approach. The evidence is that the traditional models of training are not as effective as organisations need and must adopt dynamic and constantly evolving learning systems to be competitive.

Theme 3: Technology-Mediated Learning and Knowledge Platforms

Technology mediated learning is one of the facilitators of the workforce transformation. Intelligent tutoring systems, learning management systems and analytics-driven learning systems are becoming increasingly popular as AI-based systems that can be used to personalise and optimise learning processes. Ramachandran et al. (2024) show that AI-based training is more interactive and knowledge retaining as it alters the learning content to be presented depending on the needs of the specific user. Similarly, other studies cite the reality that digital tools can provide real-time feedback, determine the skill gap, and adaptive learning paths. Remarkably, all three dimensions of the AMO framework are contributed by the systems. Some of their strategies that are able to enhance their abilities include targeted skill development, ability-enhancing motivation strategies, such as creating collaborative learning environments and flexible learning environments, and ability-enhancing opportunity creation strategies, which include the creation of collaborative learning environments, as well as flexible learning environments. This compounding impact points to the strategic importance of technology in evolution of the contemporary labour force.

Theme 4: Organisational Performance Outcomes

The reviewed studies provide a good evidence that reskilling and upskilling programs positively affect the organisational performance. The outcomes include high productivity, capability to be innovative, flexible workforce and employee retention. The research at the firm level (e.g., Damioli et al., 2021; Babina et al., 2024) suggests that the adoption of AI is connected with the promotion of productivity and innovation, particularly when they are supported by the good workforce development strategies. Similarly, case-specific studies (e.g., Mamela et al., 2020; Khushk et al., 2026) also focus on the idea that reskilling has the ability to assist in the process of increasing operational efficiency and career growth. Also, as Mahade et al. (2025) also show, AI-driven HR practices can improve decision-making and lead to sustainable organisational performance. All of these findings provide a good rationale as to why workforce development is not just a support activity but a highly important driver of competitive advantage in the AI-driven settings.

Theme 5: Challenges and Barriers

Even with the advantages, the literature has found that there are a number of unresolved issues that impede the successful reskilling and upskilling. These are the rapid obsolescence of skills, high implementation cost, resistance to change and lack of leader support. The literature on SMEs and developing countries (e.g., Vidas-Bubanja et al., 2023) points to the structural barriers, i.e., limited access to digital infrastructure and training materials. Moreover, Revtiuk and Pawlowska-Nowak (2025) demonstrate that the shortage of skills can not only lead to the adoption of AI, but also create new gaps of competence, which will result in a paradoxical situation. Also, ethical issues, such as data privacy and algorithmic bias, are also viewed as critical concerns, especially in AI-based HR systems. These issues indicate that effective workforce change must be supported not only by technology investment but also by institutional support, the policy framework, and the cultural change.

3.3 Quantitative Overview

The quantitative map of the identified literature shows an evident and rapidly increasing expansion in the academic interest in AI-driven reskilling and upskilling of the workforce. In Figure 2 and Table 2, the temporal distribution shows that the activity of research was comparatively low between 2015 and 2018 but significantly increased in 2019 and further on, the number of studies published after 2022 increased dramatically.

This tendency indicates the increasing influence of the implementation of AI, automation, and digital transformation in industries, as well as the increasing impact of post-pandemic digitalisation. The recent explosion in the literature implies that organisations and researchers are beginning to acknowledge workforce reskilling as a key strategic response to technological disruption as opposed to a marginal HR practice.

The diffusion of studies, along with the evolution of time, evidence the shift of the direction of research. The previous research has been mostly focused on the risks of automation and labour displacement (e.g., Autor, 2015; Acemoglu and Restrepo, 2020), whereas more recent studies have been focused on organisational strategies, the learning systems that are facilitated by AI, and workforce adaptability. This development would mean that it would shift to problem based perspective (job loss) and solution based perspective (capability development and performance enhancement).

This shift is also supported by the concept-frequency analysis. The fact that the number of terms like AI skills, digital competencies, lifelong learning, and human capital development are frequently found in the literature is indicative of the fact that the literature has since outgrown the isolated training concerns to an overarching focus on strategic workforce transformation. The growing significance of HR analytics and AI-based HRM activities also demonstrate the growing presence of technology in workforce management practices.

In general, the quantitative trends demonstrate that AI-driven reskills has become a key research area, with its rapid growth, diversification as a theme, and increasing theoretical sophistication. Figure 2 demonstrates the methodological and time trends.

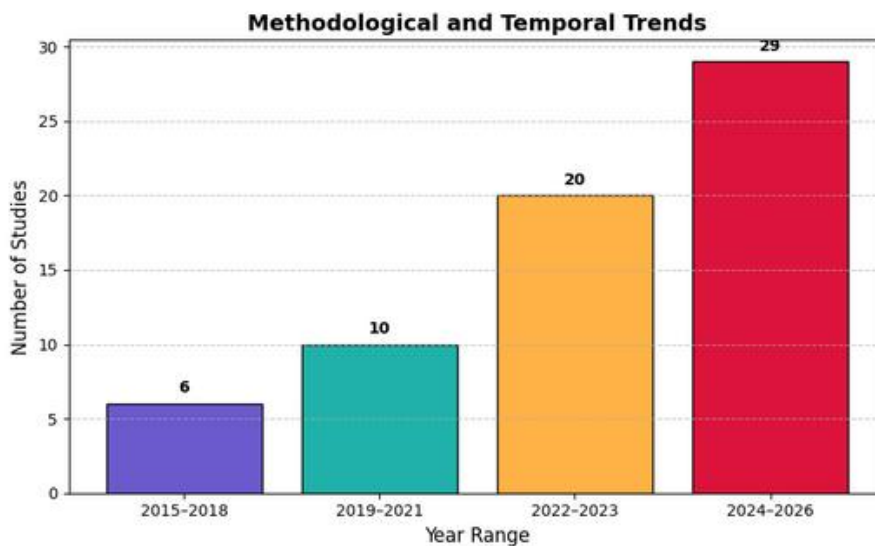


Figure 2. Methodological and Temporal Trends

Table 2 provides the corresponding year-wise distribution and representative studies supporting this trend.

Table 2. Methodological and Temporal Trends

Year Range	Number of Studies	Representative Examples
2015–2018	6	Bleady et al., 2018; Guenole et al., 2018; Wuttaphan, 2017
2019–2021	10	Diaz & Halkias, 2021; Mahboubi & Mokaya, 2021; Padmaja & Mukul, 2021
2022–2023	20	Ng et al., 2023; Morandini et al., 2023; Haverland et al., 2023
2024–2026	29	Achoki, 2023; Khushk et al., 2026; Madanchian &

	Taherdoost, 2025; Egasmara et al., 2025
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Table 3. Key Concepts and Theoretical Frameworks

Key Term / Framework	Frequency (% of Studies)	Representative Sources
AI skills / digital skills	83%	Ramachandran et al., 2024; Kanagarla, 2024; Tariq, 2024
Lifelong learning	76%	Hajam & John, 2024; Ng et al., 2023; Padmaja & Mukul, 2021
Reskilling / upskilling	74%	Asiedu & Tenakwah, 2025; Appiah, 2025; Farawowan, 2025
HR analytics / AI in HRM	61%	Al Samman & Al Obaidly, 2024; Fenwick et al., 2024; Egasmara et al., 2025
Digital competence frameworks	57%	Benayoune, 2024; Santana & Díaz-Fernández, 2023
Human capital theory	31%	Wuttaphan, 2017; Mahboubi & Mokaya, 2021
Dynamic capabilities theory	26%	Bleady et al., 2018; Morandini et al., 2023
Ability–Motivation–Opportunity framework	22%	Babashahi et al., 2024; Appiah, 2025; Haverland et al., 2023

3.4 AMO-Based Synthesis of Findings

The application of the Ability -Motivation-Opportunity (AMO) framework will provide an integrative and structured perspective with the aim of synthesising the findings of the selected research. The framework demonstrates the manner in which the AI-based organisational strategies are further translated into workforce capability development and ultimately, the performance outcomes.

The discussion indicates that the basis of transforming the workforce is the ability enhancing practices. Employees can be assisted in acquiring technical and cognitive skills necessary in an AI-driven environment through the use of AI-driven training programs, digital learning platforms and structured competency frameworks. These are highly consistent with the Human Capital Theory that has been used to underscore the importance of skill development as a crucial contributor to productivity and organisational competitiveness. Notably, the literature suggests that the ability development is no longer associated with technical expertise but with adaptive and interdisciplinary competencies.

Simultaneously, motivational-boosting practices are essential in maintaining the engagement and participation of employees in reskilling programs. Research indicates that recognition systems, incentive schemes that are career-linked and AI-driven feedback systems are essential in promoting both intrinsic and extrinsic motivation. Engagement can also be achieved by enhancing interaction and personalisation of learning by the use of gamified learning environment and real-time performance tracking. These results are consistent with Organisational Learning Theory which focuses on the continuous learning and knowledge sharing as the most important organisational processes.

The third dimension, opportunity-enhancing practices, is needed in order to make sure that the acquired skills are efficiently used within the organisational settings. Flexible job descriptions, working cross-functionally and working environments that are innovation-focused allow employees to put new competencies into meaningful practices. These practices are directly related to the Dynamic Capability Theory which reveals how organisations reconfigure resources and capabilities in order to adapt to changing environments. The results are that reskilling initiatives might not be converted to performance gains unless sufficient opportunities to practice skills are provided.

Notably, the synthesis shows that the three AMO dimensions are interrelated, as opposed to being independent of one another. A good workforce transformation is achieved when organisations at the same time invest in skill building, motivation to employees and supportive structures. This integrated approach will help organisations transform AI-driven strategies into tangible results, such as enhanced productivity, innovation, and organisational resilience. This synthesis is presented in table 4.

The concept-frequency analysis shows that the most prevalent constructs are AI skills, digital skills, lifelong learning, HR analytics and human capital development. This validates the fact that there is a shift out of the training narrow issues into strategic transformation of the workforce which is capabilities-based. The key ideas and theoretical approaches are summarised in table 3.

Table 4. Mapping Findings on AMO Framework

AMO Dimension	Practices Identified in Literature	Theoretical Link	Outcome
Ability-enhancing	AI-driven training programs, mentorship models, microlearning, and digital literacy initiatives (Ramachandran et al., 2024; Ikhsan et al., 2025).	Human Capital Theory	Builds technical and cognitive competence; reduces skill obsolescence.
Motivation-enhancing	Recognition systems, gamified learning, career-linked rewards, and AI-based progress tracking (Chandrakant, 2023; Appiah, 2025).	Organisational Learning Theory	Strengthens intrinsic engagement and long-term participation.
Opportunity-enhancing	Flexible roles, cross-functional collaboration, and project-based innovation labs (Asiedu & Tenakwah, 2025; Egasmara et al., 2025).	Dynamic Capability Theory	Translates skills into innovation and performance gains.

, the results indicate that the successful reskilling during the AI-era will be based on the ability to include the strategic HRM, flexible learning mechanisms, motivation of the employees and the ability to use the skills. Another suggestion in the findings is that the most effective approach to conducting the workforce development is to consider reskilling and upskilling as ongoing, technology-intensive, and strategically-oriented processes, rather than as single-training processes.

3.5 Integrated Interpretation of Results

In addition to the individual themes, the fact that AI-based workforce transformation is a systemic and multi-level process is apparent. On the macro level, the technological changes transform the labour markets and skills demanded, whereas on the organisational level, the changes are mediated by the HR strategies and learning systems. Individually, employee attitudes, motivation and adaptability are the determinants of how effective reskilling initiatives are.

The main revelation that the analysis presents is the move towards the episodic training intervention to the system of continuous capability development. Reskilling of organisations is becoming more and more entrenched within the overall organisational strategic frameworks, with AI technologies, HR practices and learning mechanisms, being integrated into a single system. This change is indicative of a shift towards learning organisations, in

which workforce development is continuous, responsive and aligned towards organisational goals.

The other significant finding is the development of a feedback loop between the adoption of AI and the development of workforce. Even though the adoption of AI will mean that the organisation will need new skills, effective reskilling will lead to an organisation that is better placed to adopt and leverage AI technologies.. This two-way process implies that the workforce development and technological innovation are two mutually reinforcing processes. Lastly, the findings show the relevance of contextual factors, such as the size of the organisations, the nature of the industry, as well as regional variations. Large organisations are more likely to embrace structured and technology based learning systems whereas the SMEs tend to adopt more flexible and resource constrained learning systems. On the same note, developed economies are at a higher level of AI adoption, with developing regions being faced with infrastructural and capability constraints.

4. Discussion

The results indicate that reskilling and upskilling of the workforce in AI times have become strategic organisational priorities and not alone training programs. The chosen articles summarised in Table 1 reveal that organisations are starting to consider workforce development in line with the adoption of AI, with the focus being on building trust, leadership support, and learning culture as the main drivers of change (Appiah, 2024; Appiah, 2025; Hasan et al., 2024). This is in line with Human Capital Theory that considers skill development as an investment that increases productivity and organisational performance (Wuttaphan, 2017).

Meanwhile, the outcomes indicate the topicality of the Dynamic Capability Theory, because organisations have to restructure the skills of the workforce to adapt to the technological shift (Bleady et al., 2018). Companies which actively integrate reskilling strategies are more adaptive and have better performance results (Khushk et al., 2026; Vidas-Bubanja et al., 2023). This is also supported by the upward trend in the number of research activities as in Figure 2, and Table 2 presents the distribution of the same, which has been increasing with the time, reflecting the rising significance of AI-driven workforce transformation.

The results are also consistent with Organisational Learning Theory, which underlines the paradigm change towards an ongoing learning model with the help of AI-based platforms (Koka, 2024). Organisational learning systems and online training environments, as well as knowledge-sharing activities, are increasingly being adopted by organisations to continue to develop their capabilities (Ng et al., 2023; Cabrera et al., 2025). The patterns of human capital development, digital skills and lifelong learning conceptualised in Table 3 also identify the predominance of digital proficiency, lifelong learning, and human capital development in the literature.

The use of the AbilityMotivationOpportunity (AMO) framework helps to give an organized account of how organisations can convert the reskilling initiatives into performance results (Joseph, 2024). The concept of ability-enhancing practices aims to train skills using AI-enabled training systems, whereas the motivation-enhancing practices are concerned with engaging employees, trusting them, and rewarding them (Appiah, 2024; Ramachandran et al., 2024). The opportunity-enhancing practices mean that the employees are able to use the skills that have been acquired with the help of favourable organisational structures and teamwork (Asiedu and Tenakwah, 2025; Egasmara et al., 2025). Comparative study shows disparities in organisational strategies. Big companies tend to use structured and technology-based systems to learn in line with strategic objectives and SMEs in line with flexible and adaptive systems owing to the lack of resources (Fenwick et al., 2024; Iyelolu et al., 2024). Likewise, established economies are more inclined toward AI implementation because of the superior infrastructure, and the emerging ones experience difficulties yet have a high potential of changing the workforce (Vidas-Bubanja et al., 2023). The variations in HR strategies also arise, with the centralised systems having a tendency towards standardisation, whereas the

adaptive systems are more oriented towards flexibility and personalisation (Hajam & John, 2024).

Based on these findings, this research suggests a theoretical knowledge where the AI strategy motivates AMO-based practices, which result in workforce competence and enhanced organisational performance. Figure 4 depicts this relationship and shows how the adoption of AI can lead to the development of capabilities through organized HR practices.

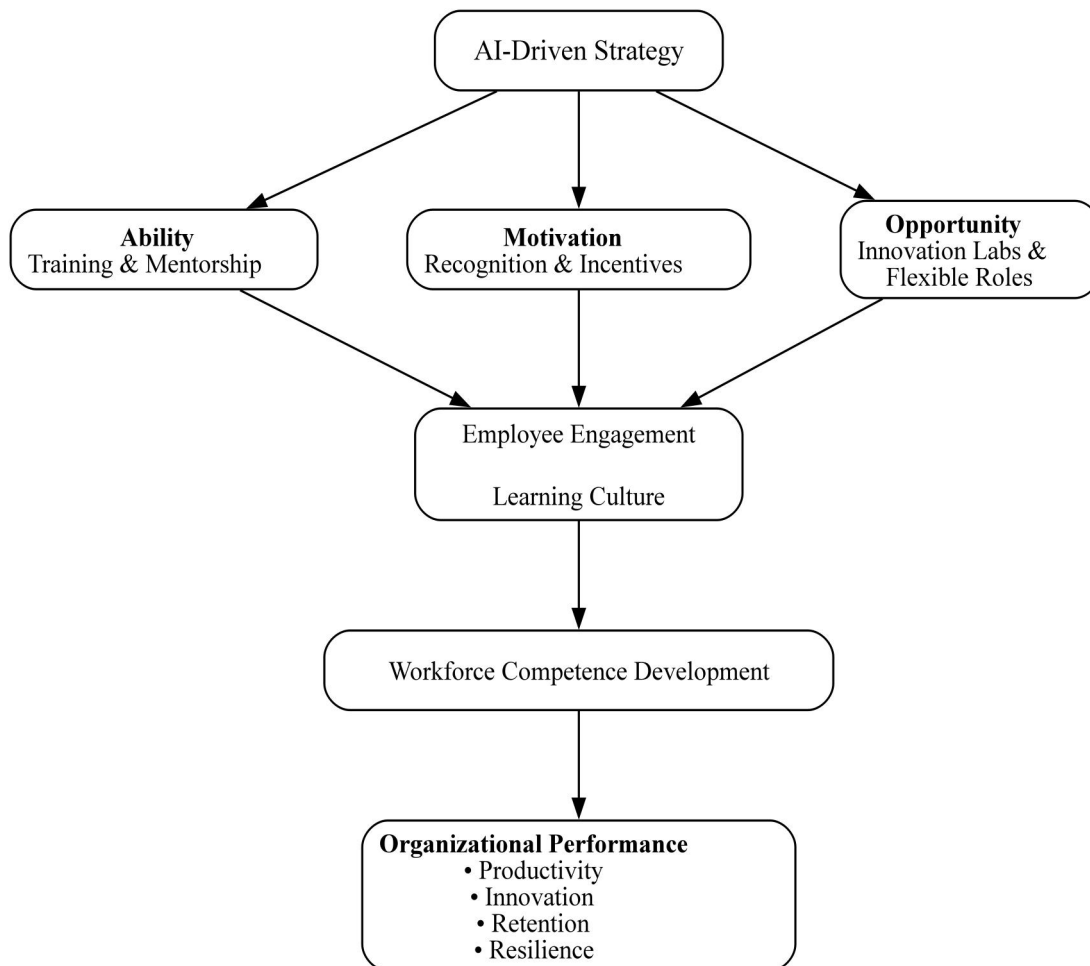


Figure 4. AI-Enabled Workforce Transformation Framework

Although these contributions have been made, there are some research gaps. Longitudinal research on long-term transformation of the workforce, little emphasis on developing economies, and minimal attention to ethical aspects of AI-based systems, including bias and data privacy are missing (Madanchian and Taherdoost, 2025). These gaps need to be filled in order to promote research and practice in this area.

On the whole, the discussion agrees that strategic HRM, a system of continuous learning, and supportive organisational environment should be incorporated in order to effect successful workforce transformation. The overall knowledge gained by Table 1, Table 4, and Figure 4 allows making a consistent idea of how organisations can effectively apply reskilling and upskilling in the AI era.

5. Conclusion

The paper provides a syntactic overview of AI-based workforce reskilling and upskilling, their rising strategic importance in contemporary organisations. The findings suggest that reskilling and upskilling ceases to be the roles associated with operational training but

evolved into the roles that facilitated the organisational adaptability, innovation and performance. In particular, the use of AI-based HR solutions, such as customised learning platforms, online training platforms, and data-driven workforce planning, have played a significant role in the effectiveness of skill development programs and helped to continue the change of the workforce. In theory, the study has contributed in the formulations of an integrated AMO based framework that explains how organisations can convert reskilling strategies to performance results by engaging in the alignment of the ability, motivation and opportunity enhancing practices. The study which is a synthesis of the knowledge of the Human Capital Theory, Dynamic Capability Theory and Organisational Learning Theory offers a clear view of how the development of the workforce can be of benefit in organisational competitiveness in the AI era. The study also has great practical implications. The results show the significance of correlating reskilling plans with organisational objectives and the establishment of the continuous learning culture in the presence of HR leaders. In the case of organisations, the findings indicate the significance of investing in AI-enabled learning systems and facilitating settings to facilitate the use of skills. To policymakers, the study highlights the importance of funding workforce development by training them, equipping them with digital infrastructure, and policies that overcome skill gaps. Nevertheless, there are some limitations of the study. The use of pre-chosen databases could have limited the amount of literature used and regional clustering of studies could limit generalisability. Moreover, lack of empirical validation of the proposed framework creates a need to conduct further studies. Future studies need to be longitudinal in order to investigate long-term effects of reskilling programs, use more mixed-method designs to gain a more in-depth perspective, and conduct cross-sector comparisons to determine the workforce transformation specific to the industry.

References

1. Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of political economy*, 128(6), 2188-2244.
2. Achoki, P. M. A. (2023). Upskilling and reskilling for a VUCA world: organizational sense-response framework. *GiLE Journal of Skills Development*, 3(2), 34-52.
3. Adio, S. A., Sikhakhane-Nwokediegwu, Z., Erinjogunola, F. L., Ajiroto, R. O., & Olayiwola, R. K. (2025). Integrating AI in Public Transport Workforces: A Review of HR Challenges and Opportunities. *INTERNATIONAL JOURNAL*, 6(2), 611-624.
4. Ahmed, B. (2024). Bridging disciplines: How multidisciplinary research advances innovation. *Kashf Journal of Multidisciplinary Research*, 1(08), 389-399.
5. Akindoyin, D. I., & Akuche, C. C. (2023). Analysis of development prospect and security crisis in Nigeria. *Lead City Journal of the Social Sciences (LCJSS)*, 8(2), 1-16.
6. Al Samman, A. M., & Al Obaidly, A. A. A. (2024, January). AI-driven e-HRM strategies: Transforming employee performance and organizational productivity. In *2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETISIS)* (pp. 23-29). IEEE.
7. Appiah, R. I. (2024). Public Perception and Confidence: How Workforce Attitudes towards AI Influence Willingness to Engage in Upskilling or Reskilling Initiatives. *International Journal of Emerging Trends in Computer Science and Information Technology*, 5(4), 116-124.
8. Appiah, R. I. (2025). Corporate Strategies for Successful Workforce Upskilling and Reskilling in Response to AI Adoption-What Works, What Does not, and Why. *International Journal of Emerging Research in Engineering and Technology*, 6(1), 91-99.
9. Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, 159, 157-160.
10. Asiedu, E., & Tenakwah, E. S. (2025). Future-proofing your workforce: upskilling and reskilling as HR's top priorities. *Strategic HR Review*, 24(4), 169-173.

11. Asif, M., Mondal, A., Soumil, S., Das, A., Sahoo, P., Kumar, R., ... & Mahapatra, A. (2024). Augmented reality and virtual reality in education: A transformative journey into immersive learning environments. *Advances in Computational Solutions*, 185.
12. Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of economic perspectives*, 29(3), 3-30.
13. Babashahi, L., Barbosa, C. E., Lima, Y., Lyra, A., Salazar, H., Argôlo, M., ... & Souza, J. M. D. (2024). AI in the workplace: A systematic review of skill transformation in the industry. *Administrative Sciences*, 14(6), 127.
14. Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151, 103745.
15. Bauer, E., Greisel, M., Kuznetsov, I., Berndt, M., Kollar, I., Dresel, M., ... & Fischer, F. (2023). Using natural language processing to support peer-feedback in the age of artificial intelligence: A cross-disciplinary framework and a research agenda. *British Journal of Educational Technology*, 54(5), 1222-1245.
16. Benayoune, A. (2024). Competency-based framework development and implementation: Current and future perspectives. *Information Management and Business Review*, 16(3), 606-615.
17. Bessen, J. (2018). Artificial intelligence and jobs: The role of demand. In *The economics of artificial intelligence: an agenda* (pp. 291-307). University of Chicago Press.
18. Bleadly, A., Ali, A. H., & Ibrahim, S. B. (2018). Dynamic capabilities theory: pinning down a shifting concept. *Academy of Accounting and Financial Studies Journal*, 22(2), 1-16.
19. Cabrera, B. C. C., Leal, M. C., Martínez, J. A. S. A., Soto, A. L. R., Sepulveda, J., Valencia, J., ... & Valencia-Arias, A. (2025). Artificial intelligence (AI) and learning management systems (LMS): A bibliometric analysis. *Journal of infrastructure, policy and development*, 9(1), 8029.
20. Chandrakant, N. (2023). Gamified learning and NLP: Enhancing student engagement through AI-driven interactive education models. *International Journal of Science and Research Archive*, 9(1), 813-824.
21. Crogman, H. T., Cano, V. D., Pacheco, E., Sonawane, R. B., & Boroan, R. (2025). Virtual reality, augmented reality, and mixed reality in experiential learning: Transforming educational paradigms. *Education Sciences*, 15(3), 303.
22. Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review*, 11(1), 1-25.
23. Diaz, J., & Halkias, D. (2021). Reskilling and upskilling 4IR leaders in business schools through an innovative executive education ecosystem: An integrative literature review. *Available at SSRN 3897059*.
24. Egasmara, F., Rahayu, A., Wibowo, L. A., Rofaida, R., Sofia, A., & Fauziyah, A. (2025). Workforce planning optimization utilising AI to improve firm performance: a systematic literature review using VOSviewer. *Journal of Work-Applied Management*, 1-13.
25. Ekuma, K. (2023). Rethinking Upskilling and Reskilling in the Age of AI and Automation: A fsQCA Approach.
26. Elly, B., Klaus, D., & Lostar, E. (2025). Overcoming Barriers to AI Adoption in Workforce Development.
27. Farawowan, F. F. (2025). Upskilling and Reskilling: Adaptive Strategies For HR Management in Facing The Industrial Revolution 5.0. *Oikonomia: Journal of Management Economics and Accounting*, 2(4), 49-57.
28. Fenwick, A., Molnar, G., & Frangos, P. (2024). The critical role of HRM in AI-driven digital transformation: a paradigm shift to enable firms to move from AI implementation to human-centric adoption. *Discover Artificial Intelligence*, 4(1), 34.
29. Fossen, F., & Sorgner, A. (2019). Mapping the future of occupations: Transformative and destructive effects of new digital technologies on jobs. *Форсаїм*, 13(2 (eng)), 10-18.

30. Graetz, G., & Michaels, G. (2015). *Robots at work* (No. Center for Economic Performance. Discussion Paper No. 1335). London: Centre for Economic Policy Research.
31. Guenole, N., Lamb, C., & Feinzig, S. (2018). Competencies in the AI era. *IBM Talent Management Solutions*.–2018.–6 p.
32. Hajam, A. A., & John, A. S. (2024). Reskilling and Upskilling Strategies in the Era of Automation: A Human-Centered Approach to Workforce Development. *International Journal of Multidisciplinary Research Transactions*, 6(10).
33. Hasan, M., Haque, M. A., Nishat, S. S., & Hossain, M. M. (2024). Upskilling and reskilling in a rapidly changing job market: Strategies for organizations to maintain workforce agility and adaptability. *European Journal of Business and Management Research*, 9(6), 118-126.
34. Haverland, S., Halkias, D., & Diaz, J. (2023). Critical Success Factors for Reskilling and Upskilling Engineer Leaders in Customized Executive Education Programs: An Integrative Literature Review. Available at SSRN 4434273.
35. Ikhsan, I., Husnaini, A. N., & Lopo, F. L. (2025). Strategies for implementing ai in LMS to improve the effectiveness and personalization of digital learning. *The Journal of Academic Science*, 2(3), 944-953.
36. Istenič, T., Zupan, N., Česnik, M., Nosan, E. G., & Podpeskar, N. (2022). Reskilling and upskilling in support of company competitiveness. *Metaversing The Corporate Strategy: The Opportunities and Challenges of Digital*, 225-243.
37. Iyelolu, T. V., Agu, E. E., Idemudia, C., & Ijomah, T. I. (2024). Driving SME innovation with AI solutions: overcoming adoption barriers and future growth opportunities. *International Journal of Science and Technology Research Archive*, 7(1), 036-054.
38. Jamal, A. F., El Nemar, S., & Sakka, G. (2025). The relationship between job redesigning, reskilling and upskilling on organizational agility. *EuroMed Journal of Business*, 20(2), 474-492.
39. Joseph, S. (2024). Organizational Workforce Management in the Digital Age: The Role of Technocultural Interventions in Mitigating the Negative Impacts of AI-Driven Technological Change. *Archives of Current Research International*, 24(10), 10-9734.
40. Kanagarla, K. (2024). Artificial Intelligence and Employment Transformation: A Multi-Sector Analysis of Workforce Disruption and Adaptation. Available at SSRN 5015970.
41. Kawa, M. (2025). The Future of Skills and Labor Market in the Age of AI. *Studia ad Didacticam Scientiarum Socialium Pertinentia*, 424(15).
42. Khushk, A., Zhiying, L., Yi, X., & Aman, N. (2026). AI-driven HR transformation in Chinese automotive industry: strategies and implications. *Business Process Management Journal*, 32(1), 30-50.
43. Koka, N. A. (2024). An Insight into the Efficiency of Artificial Intelligence (AI)-Chatbot as Digital Tutors for Enhancing Learners' Motivation and Performance in Linguistics Courses. *Pakistan Journal of Life & Social Sciences*, 22(2).
44. Kromann, L., Malchow-Møller, N., Skaksen, J. R., & Sørensen, A. (2020). Automation and productivity—a cross-country, cross-industry comparison. *Industrial and Corporate Change*, 29(2), 265-287.
45. Madanchian, M., & Taherdoost, H. (2025). Barriers and Enablers of AI adoption in human resource management: a critical analysis of organizational and technological factors. *Information*, 16(1), 51.
46. Mahade, A., Elmahi, A., Alomari, K. M., & Abdalla, A. A. (2025). Leveraging AI-driven insights to enhance sustainable human resource management performance: moderated mediation model: evidence from UAE higher education. *Discover Sustainability*, 6(1), 1-22.
47. Mahboubi, P., & Mokaya, M. (2021). The skills imperative: Workforce development strategies post-COVID. *CD Howe Institute Commentary*, 609.

48. Mamela, T. L., Sukdeo, N., & Mukwakungu, S. C. (2020, August). Adapting to artificial intelligence through workforce re-skilling within the banking sector in South Africa. In *2020 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD)* (pp. 1-9). IEEE.
49. Minbaeva, D. (2021). Disrupted hr?. *Human Resource Management Review*, 31(4), 100820.
50. Morandini, S., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D., & Pietrantonio, L. (2023). The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations. *Informing Science*, 26, 39-68.
51. Nedelkoska, L., & Quintini, G. (2018). Automation, skills use and training. *OECD Social, Employment and Migration Working Papers*.
52. Ng, D. T. K., Leung, J. K. L., Su, J., Ng, R. C. W., & Chu, S. K. W. (2023). Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. *Educational technology research and development*, 71(1), 137-161.
53. Padmaja, V., & Mukul, K. (2021). Upskilling and reskilling in the digital age: the way forward for higher educational institutions. In *Transforming higher education through digitalization* (pp. 253-275). CRC Press.
54. Ramachandran, K. K., Srivastava, A., Panjwani, V., Kumar, D., Cheepurupalli, N. R., & Mohan, C. R. (2024). Developing AI-powered training programs for employee upskilling and reskilling. *Journal of Informatics Education and Research*, 4(2), 1186-1193.
55. Revtiuk, Y., & Pawlowska-Nowak, M. (2025). Skills Shortages as a Driver of AI Adoption: Evidence from Developed Countries.
56. Santana, M., & Díaz-Fernández, M. (2023). Competencies for the artificial intelligence age: visualisation of the state of the art and future perspectives. *Review of Managerial Science*, 17(6), 1971-2004.
57. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California management review*, 61(4), 15-42.
58. Tariq, M. U. (2024). The role of AI in skilling, upskilling, and reskilling the workforce. In *Integrating generative AI in education to achieve sustainable development goals* (pp. 408-420). IGI Global Scientific Publishing.
59. Tariq, M. U., Poulin, M., & Abonamah, A. A. (2021). Achieving operational excellence through artificial intelligence: Driving forces and barriers. *Frontiers in psychology*, 12, 686624.
60. Vidas-Bubanja, M., Bogetić, S., Bešić, C., Kalinić, Z., & Bubanja, I. (2023). Managing the reskilling revolution for the digital age: Case study-western Balkan countries. *Journal of Engineering Management and Competitiveness*, 13(1), 37-52.
61. Wuttaphan, N. (2017). Human capital theory: The theory of human resource development, implications, and future. *Life Sciences and Environment Journal*, 18(2), 240-253.