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Workforce Up-Skilling Strategies for Artificial Intelligence (AI) Integration in Business Operations: Perspectives for Emerging Market

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Abstract

This study critically assessed workforce upskilling strategies for AI integration in business operations as a broad objective, specifically, the study sought to identify various methods of training and development for Al adoption in business operations and to review challenges and opportunities of re-skilling and cross-training for Al process re-engineering in business operation. A qualitative research method was adopted and secondary qualitative data utilized and analyzed through thematic analysis. This study determined the various methods of training and development for Al adoption, the challenges and opportunities of re-skilling and cross-training for Al process re-engineering in business operations. Findings revealed that modern training methodologies which includes a blend of various methods such as traditional and technology-driven learning, on-the-job training (OJT), and e-learning, are essential for making AI more accessible and for overcoming psychological barriers like anxiety and resistance to change. The study also revealed that challenges affecting re-skilling and cross-training for AI reengineering include lack of support from senior management, inadequate financial resources, and employee resistance to change. However, opportunities that exist include creation of more agile and efficient workforce and human-AI collaboration, personalized learning and cost reduction. The study concluded that T&D, re-skilling and cross-training, are effective upskilling strategies that can enable AI integration in business operations. The study is limited by the fact that it relied solely on secondary qualitative data which fails to collect context specific data, hence, limiting the generalizability potential of the study, given that fact that it lacks empiricism.

Keywords: *Workforce Up-skilling, AI integration, AI re-engineering, Emerging Markets, Re-skilling and Cross-Training, Business Operations*

INTRODUCTION

Globally, the businesses environment is undergoing tremendous changes. In the labor market, there is a growing consensus that the most successful organizations in the nearest future will be those that invest in upskilling their workforce (Li, 2024). Organizations that want to stay abreast of these modern challenges and have competitive advantage must be ready to equip their workforce with the skills needed to respond to these changes. One of the major strategy that can be adapted to enable employees easily adapt to these constant changes is continuous development of employees skills (Muchiri, 2020). Businesses that want to maintain competitiveness, penetrate new markets and expand are required to evolve their workforce, through upskilling programs which are in line with these recent technological innovations such as Artificial Intelligence (AI) (Shokran, Islam, Fedousi, 2025).

Upskilling of business workforce is essential in the context of rapid technological advancement and digital transformation (Li, 2024). The integration of new technologies has affected 86% of firms, causing an extensive of workplace competencies (Adepoju & Aigbavboa, 2020). This shift influences skills, knowledge, experience, capabilities, and attitudes as employees tend to adjust to greater levels of automation, and AI usage (Adepoju & Aigbavboa, 2020). Traditional methods of workforce planning are the foundations for upskilling employees. However, these methods are constrained by factors such as dependence on outdated data and strategies which may not be relevant to current context. Over reliance on such methods can affect an organization's effort to achieve objectives in this present environment, limit their ability to predict future talent needs, identify skill gaps and even manage succession planning (Hussain, Khan, Rakhmonov, Mamadiyarov, Kurbonbekova, & Mahmudova, 2023). Technological advancements and recent innovations, emergence of hybrid and remote work type, drift in expectations of employees, global workforce demands, have created a huge gap and complexity of workforce dynamics which needs to be covered and tackled. Organizations now need more agile and data-driven approaches to workforce planning that can address these complexities and cover gaps in real time (Arya, Gaur, Dadwal & Kalra).

The adoption and integration of Al tools into workforce planning is seen as a solution to these challenges (Guerra, Danvila-del-Valle & Méndez-Suárez, 2023). However, despite growing interest in using Al for workforce management, many businesses still struggle to effectively integrate and utilize these tools for proactive business processes, most often, this could be because their workforce lack the necessary skills needed to integrate AI into their business functions. There remains a significant gap in understanding the various upskilling strategies that can be adopted while integrating Al technologies for efficient and effective business processes. If these challenges are not addressed, businesses may find it difficult to fully benefit from the numerous advantages that Al offers for improving their operations. Employees will also not have the necessary skills required of them in the present global workforce or meet specific industry demands. If this persists for a longer time, these businesses may have workers who cannot meet up with current skill set, making business operations and processes to be outdated, which in turn can affect the overall performance of such business, hence, necessitating this study. This study seeks to examine workforce upskilling strategies for AI integration in business operations in Nigeria. Specifically, the study seeks to:

1. Identify various methods of training and development for Al adoption in business operations.
2. Review challenges and opportunities of re-skilling and cross-training for Al process re-engineering in business operations.

REVIEW OF RELATED LITERATURE

Workforce Upskilling Strategy

The concept upskilling can be described as the practice of improving or upgrading the existing skills of employees in an organization, in other to enhance their performance in carrying out their tasks and also to meet the ever dynamic nature of demands (Hajam & John, 2024; Hasan, Haque, Nishat, & Hossain, 2024; Muchiri, 2022; Ruíz-Valdés, Ruíz-Tapia, & Gómez-Chagoya, 2023). Some of these skills include acquiring "soft" skills like emotional intelligence for leadership in hybrid work environments or obtaining new technical skills to stay relevant with market developments and trends (Hasan et al., 2024).

The conceptual and hypothetical implications of upskilling are that it is focused on improving the flexibility and adaptability of employees in facing whatever outcomes they may encounter on the job. Hasan et al. (2024) is of the view that there is an obvious connection between these three key components: Strategies for Upskilling and Re-skilling (SUR), the Organizational Support Environment (OSE), and Workforce Agility and Adaptability (WAA). In recent times, upskilling is now seen as more or less a direct response to the Fourth Industrial Revolution and the proliferation of AI (Hajam & John, 2024; Li, 2024). Current bibliometric data asserts that since 2022, there have been a hike of about 23% increases in up-skilling related researches, a trend which has been linked to emergence of AI and its various tools (Hajam & John, 2024).

The ability of an organization to retain talent and invest in employee development is crucial (Ruíz-Valdés et al., 2023). It has been demonstrated that most workers feel appreciated when they believe the organization they work so hard for is interested in their professional and personal development, as this can lead to better opportunities. Through mentorship programs, this proactive approach to talent development and motivation is put into practice, creating a sense of purpose and belonging that is essential for employee engagement (Muchiri, 2022). By addressing skills gaps internally, organizations can lower staff turnover and avoid expensive external hiring, resulting in a stable and productive workforce (Muchiri, 2022).

Training and Development

Training and Development are two concepts that are used interchangeable in certain context. However, their meaning varies. Formally, training is explained as an educational process that is aimed at providing persons (employees in this context) with the foundational knowledge, skills and expertise required for performance in their current (Muchiri, 2022). This may involve training like new hire on boarding, technical skills training, or compliance training, whose basic aim is improved near-term productivity and efficiency (Hussain et al., 2023). "Development" is a more general term with the goal of developing an employee's personality as a whole and getting him ready for challenges later on, career growth, and long-term organizational objectives (Muchiri, 2022). While training establishes the foundations and establishes the minimum standard of capability, development takes the next step to propel individual and career progression (Disprz, 2024).

With important turning points like Hoe and Company's founding of a formal training school in 1872, the structuring of T&D started in the late 19th and early 20th centuries. Virtual instructor-led training (VILT) and self-paced e-learning, which offer more flexibility and opportunities for active learning, have been introduced as a result of the digital age, which is being driven by the proliferation of smartphones and internet management systems. In order to meet the demands of a dispersed workforce, businesses are now implementing a hybrid training, video conferencing, and learning model that combines the advantages of in-person meetings with the adaptability of online education. (Hussain and others, 2023). Performance metrics, T&D programs have been shown to have a profound impact on employee engagement, satisfaction, and retention (Alrazehi, Amirah, & Emam, 2021; Tizikara & Mugizi, 2017). Employees become more committed and loyal when their development is perceived by them as being valued, which subsequently may reduce staff turnover by a considerable margin (Radhakrishnan et al., 2015; Nunkoo, 2016).

The most effective T&D interventions, thus, are those that bring these two aspects synergistically together, generating an ongoing spiral of learning that addresses short- and long-term organizational and workforce needs (Hussain et al., 2023).Various training and development methodologies should be explored to accommodate different learning preferences and organizational structures (Luna, 2025). These include in-house workshops, peer learning initiatives, online learning platforms, mentorship programs, and partnerships with universities or tech providers. Special attention should also be given to low-cost and accessible training options, recognizing that many businesses especially start-ups may not have the budget for comprehensive external consulting, thereby, fostering an internal culture of continuous learning and experimentation, where employees are encouraged to explore AI tools, share insights, and integrate innovations into their daily routines, should be encouraged (Dixit, 2024).

Artificial Intelligence (AI)

It is essential to first comprehend the terms "artificial" and "intelligence" independently in order to comprehend the idea of artificial intelligence. One way to define "intelligence" is as a mental process that includes learning, thinking, and comprehension (Lichtenthaler, 2019). However, "artificial" means something that is created by humans instead of existing naturally (Mikalef & Gupta, 2021). Combining these two allows us to define artificial intelligence as the ability of robots to mimic human intelligence (Wamba-Taguimdje,Wamba, Kamdjoug, & Wanko, 2020). AI is often understood to entail endowing a computer with human-like abilities, i.e., the ability to carry out tasks that would typically require human intelligence (Mikalef & Gupta, 2021). When machines, applications and software are deployed and structured in such a way that they start reasoning like humans, making intelligent decisions and taking the burdens from humans, to face other more complex tasks, AI is said to be in action (Arachie, Nwosu, Ugwuanyi & Muhammed, 2025).According to Eriksson, Bigi and Bonera (2020), AI mimics human performance by functioning as an intelligent agent that takes actions based on a particular comprehension of input from the environment. That is, AI aims to mimic human learning and information processing in an attempt to replicate human cognition. The phrase "cognitive technology" is frequently used to describe this skill. According to Makarius, Mukherjee, Fox and Fox (2020), cognitive technologies mimic human mental processes, allowing computers to think and behave similarly to humans. It is the ability of machines to do what intelligent humans do. This is a manifestation of the cognitive abilities of machines (Arachie Dibua & Idigo, 2023).

Artificial Intelligence Integration

Artificial Intelligence integration can be defined as the process of making machines intelligent and prompting them to function accurately in accordance to the activities of the environment (Chatterjee, Ghosh, Chaudhuri & Nguyen, 2019). In terms of functionality, AI integration is opined to mean the introduction of AI into different systems, activities and applications to improve efficiency and productivity. Precisely, the major subcomponents such as machine learning, predictive analytics, and natural language processing (NLP) are core elements of AI integration (Karalis, 2024).

Artificial Intelligence has progressed in business activities from simple, logic-based programs to more sophisticated and autonomous systems as seen in our current world (Blezek, Olson-Williams, Missert, & Korfiatis, 2021). The historical background of AI can be traced to the rule-based systems, such as ChatBots, which operated on strict, pre-programmed logical rules to perform simple tasks (Blezek et al., 2021). The 1990s marked a remarkable change in business processes with the introduction of data-driven models and neural networks, igniting the deep learning revolution and showcasing AI's transformative potential through breakthroughs like IBM Watson and AlexNet (Blezek et al., 2021). The most recent advancements, including Large Language Models (LLMs) and generative AI, have accelerated the development of a new era of "agentic AI" (Ledro, Nosella, & Dalla Pozza, 2023).

Awareness of ethical usage is very important for the successful integration of AI into any sector (Najjar, 2023). There are arguments as regards AI leading to actual biases and discrimination in organizations, endangering justice and human rights. International frameworks, like The United Nations Educational, Scientific and Cultural Organization **(**UNESCO) recommendation, highlight fundamental yet fundamental ethical principles like accountability, transparency, and fairness as a way to reduce these biases and discrimination (UNESCO, 2024). Another major issue is algorithmic biases, which have the ability to consistently favor or disadvantage particular people or groups. Hiring someone based solely on their technical expertise while ignoring those with more fundamental abilities like communication and even commitment to the task is another instance of this bias (Barocas & Selbst, 2016; Mujtaba & Mahapatra, 2019).

AI Adoption

Artificial intelligence (AI) adoption is a phenomenon that is defined as the incorporation of AI technologies into the processes, systems, and products of an organization with the goal of enhancing capabilities and efficiencies (Chatterjee, Ghosh, Chaudhuri, & Nguyen, 2019). The theoretical concept of AI implementation draws its roots from established theory constructs, led by the Technology-Organization-Environment (TOE) framework (Shahzadi, Jia, Chen, & John, 2024; Merhi & Harfouche, 2024). Another popular model is the Technology Acceptance Model (TAM) which targets end-user beliefs, i.e., "perceived usefulness" and "perceived ease of use," as the turning points for adoption behavior (Wang, Liu, & Tu, 2021; Chatterjee et al., 2021).

AI adoption by businesses has historically advanced from basic, rule-based systems to the sophisticated, self-contained platforms of today. Initial users of AI were limited to specific tasks, including early chatbots and early logic-based programs (Blezek et al., 2021). The remarkable development of data-driven machine learning and neural networks in the 1990s allowed AI to learn from experience and demonstrate its enormous commercial potential. The introduction of "agentic AI" is a hallmark of the modern era, which is driven by generative AI and enormous language models (LLMs) (Ledro, Nosella, & Dalla Pozza, 2023). One of the key arguments in literature is surrounding a persistent imbalance between workforce maturity and return of investment of upskilling programmes by managers of organizations. Also, the revolution of global at a large scale by AI innovations has caused lots of debates. It is estimated that by 2030, nearly 375 million workers or approximately 14 percent of the global workforce will have to be changed, and thus causing a pertinent impact on career paths that one person must pursue. Jobs requirements will also shift because of digitization, automation, and technological advancements in artificial intelligence. There is also an on-going subtle argument, focused on the ethics of adopting AI (Illanes, Lund, Mourshed, Rutherford & Tyreman, 2018).

Re-skilling and cross-training

Re-skilling refers to the process of educating workers on new skills with the intent to get them ready for another role or department within the same company (Rangarajan & Rubasree, 2024). On the other hand, cross-training or "cross-skilling," as some call it, is a strategy that emphasizes the training of employees in different skills so that there is greater functional flexibility in conjunction with flexible use of the labor force (Mirakyan, 2024; Karder, Beham, Hauder, Altendorfer, & Affenzeller, 2021). While re-skilling equips an employee with work in a new and novel kind of job, cross-training builds on the current worker's ability to make him competent to do varied and extra tasks, normally to support co-workers in other departments (Hernaus, Černe, & Škerlavaj, 2021). Re-skilling and cross-training lay heavy emphasis on organizational flexibility as well as human capital development concepts. According to Jamal, El Nemar, and Sakka's (2025), theoretical framework re-skilling and cross-training are components of organizational agility rather than training exercises. Formalizing these ideas is a relatively new endeavor that corresponds with the rapid advancement of technology, particularly since the Fourth Industrial Revolution began and the introduction of artificial intelligence and automation (Muchiri, 2022; Rangarajan & Rubasree, 2024).

The current emphasis on cross-training and re-skilling endevours is a response to the fact that, over the coming decades, technology will cause many professions and skill sets to change or become obsolete (Muchiri, 2022; Gruenewald & Mueller, 2025). The emergence of "agentic AI" systems with certain human abilities such as acting, reasoning, and collaborating, has given rise to the need for proactive re-skilling and cross-training initiatives(Gruenewald & Mueller, 2025). These initiatives are very necessary for companies to stay ahead of business trends and reduce redundancy.

AI Process Reengineering

The process of AI Reengineering is actually a revolutionary strategy that describes how businesses can achieve significant gains in performance metrics such as speed, quality, and cost (Thon, Finke, Kwade, & Schilde, 2021). The original Business Process Re-engineering (BPR) principles, which included "discontinuous thinking" and using contemporary information technology (IT) to realize instant results, are the foundation of AI process reengineering (Hnylianska, 2022; Subramanyam, 2021). The major tenets of BPR's entail arranging work according to results rather than tasks and establishing decision-making authority on the job itself (Popoola, Adama, Okeke & Akinoso, 2024; Bayomy, Khedr, & Abd-Elmegid, 2021). BPR's historical development can be traced back to its widespread adoption in the 1990s as a means of improving performance through drastic redesign in order to save money (Subramanyam, 2021). Information Technology played a major role in enabling early BPR by streamlining workflows and automating previously manual tasks to enhance inventory management and communication (Subramanyam, 2021; Harika et al., 2021).

This evolution of BPR has advanced with the introduction of AI-driven automation. AI-driven automation enables self-learning and self improvement, which is in contrast to traditional business process automation (BPA), which was founded on set, rule-based methodologies (Khayatbashi, Sjölind, Granåker, & Jalali, 2025). This radically alters the way processes are carried out by enabling AI to process both structured and unstructured data, including emails and documents, and to make decisions on its own in real time (Khayatbashi et al., 2025). Business activities ongoing adaptation to technological innovation is reflected in this historical shift from an emphasis on IT-enabled efficiency to one on AI and data-driven transformation.

Empirical Review

Akour, Alfaisal, Aljanada, Elhoseny, Shaalan,Salloum and Almaiah (2025) evaluated how the UAE consumers feel about integrating AI in educational settings. Included in the framework are the characteristics of acceptance, which are: perceived compatibility, trialability, relative advantage, ease of doing business, and technology export. 466 questionnaires from various universities were gathered. The research model was examined using machine learning algorithms (ML) and partial least squares-structural equation modeling (PLSSEM), which centered on the student's questionnaire responses. The IPMA was also used in this research to evaluate performance and importance of the variables. The theoretical framework of the research links the qualities of the individual variables and those of the technology which makes it new. The findings indicated that the diffusion theory factors outperform the other two factors of ease of doing business and technology export.

Hasan, Haque, Nishat and Hossain (2024) examined the effectiveness of upskilling and re-skilling initiatives in enhancing workforce agility and adaptability in a rapidly changing employment landscape. A quantitative methodology was employed to collect data by surveying 250 employees from 45 prominent companies in Bangladesh. The Study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the relationships between Strategies for Upskilling and Reskilling (SUR), Workforce Agility and Adaptability (WAA), and the Organizational Support Environment (OSE). The findings suggested that a positive organizational climate significantly influences the effectiveness of upskilling and reskilling initiatives, leading to improved employee capabilities and higher organizational performance. The report also emphasizes barriers such as insufficient financial resources and resistance to change, emphasizing the significance of tailored training programs, a culture that encourages continuous learning, and integrating modern educational materials. The Study also emphasized the need for strong leadership and organizational support in fostering a culture that highly values ongoing learning and innovation.

Dixit (2024) looked into how to acquire a deeper understanding of the opinion held by the training and development (T&D) professionals, regarding the use of artificial intelligence (AI) technology in the area of T&D. Particularly in response to the evolving needs of learners, the research aims to ascertain T&D professionals' perspective on the efficiency of AI in fostering T&D, while understanding the constraints and limitations associated with this technology. The study utilized a qualitative data. With the help of semi-structured interviews, qualitative data was collected from 21 T&D professionals. Experts working with multinational corporations (MNCs) are selected as a study sample using a convenient sampling technique. Qualitative data were analyzed using thematic analysis. Conclusions were drawn based on the results of thematic analysis. The findings of the study revealed a notable and rapid evolution in the requirements of learners, particularly during and post-COVID-19 period. AI-based technology has emerged as a significant contributor, offering learners distinct personalized experiences and enhanced convenience.

Nurlia, N., Daud, I., & Rosadi, M. E. (2023) investigated the impact of AI implementation on workforce productivity, focusing on the mediating roles of Organizational Adaptation and AI Training. The purpose of the research was to analyze how AI Implementation influences Organizational Adaptation and AI Training, and subsequently, how these factors impact Workforce Productivity within the context of the Regional Secretariat Pontianak. A quantitative approach was employed, using a sample of 70 employees through total sampling. Structural Equation Modeling (SEM) with Partial Least Squares (PLS) was used for data analysis. The finding revealed significant and positive relationship between AI Implementation, AI Training, Organizational Adaptation, and Workforce Productivity.

Muchiri (2022) in their paper discussed whether Kenyan enterprises and organizations have embraced a learning ecosystem for their employees by offering them opportunities to upskill, re-skill, and acquire new skills. An inductive reasoning approach was employed to make broad generalizations about the studied phenomenon. A mixed methodology was adopted where a survey tool comprising both open-ended and closed-ended questions was used to collect qualitative and quantitative data. A purposive sampling method proved useful in targeting expert respondents who are resourceful and knowledgeable about the subject-matter, and whose responses would yield information-rich data, while addressing the challenge of the willingness, availability, and ability of potential respondents to participate in the survey. The findings showed that in the last five years, 67.8% of Kenyan organizations had planned some form of skills training programs, although the size of the enterprise was an influencing factor with 100% of multinationals reporting to have done so while only 25.9% of microenterprises had made similar efforts.

Wang, Liu and Tu (2021) assessed the factors affecting the adoption of AI-based applications in higher education. A structural equation modeling approach was employed to investigate teachers' continuance intention to teach with AI. In the proposed model, 10 hypotheses regarding anxiety (AN), self-efficacy (SE), attitude towards AI (ATU), perceived ease of use (PEU) and perceived usefulness (PU) were tested, and this study explored how these factors worked together to influence teachers' continuance intention. A total of 311 teachers in higher education participated in the study. Based on the SEM analytical results and the research model, the five endogenous constructs of PU, PEU, SN, and ATU explained 70.4% of the changes in BI. In this model, SN and PEU were the determining factors of BI. The total effect of ATU was 0.793, followed by SE, with a total effect of 0.554. As a result, the intentions of teachers to learn to use AI-based applications in their teaching can be predicted by ATU, SE, PEU, PU and AN.

METHODOLOGY

This study utilized a qualitative approach, and data was sourced through secondary means, which allows for an in-depth examination of complex topics. This method is most suitable for this study because it enables a detailed comprehension of various methods of training and development for AI adoption. It also enables the review of challenges and opportunities of re-skilling and cross-training, for an efficient AI process re-engineering in business operations. The outlined reasons make this method most suitable for this study. The data collected spans from 2015 to 2025. The data for this research was obtained from existing published academic works, carefully selected from a variety of credible academic and industry sources. These sources include peer-reviewed articles from academic journals, accessible through well established academic journals, such as Web of Science, Google Scholar, ScienceDirect, Semantic Scholar, ResearchGate and Academia. The inclusion criteria included the consideration of only articles written within 10 years, must be peer reviewed, written in English and the full versions of the article must be available. Any paper that fell short of these criteria was excluded. This method guarantees extensive and in-depth examination of existing literature for synthesis of multi-faceted insights and empirical data on Workforce upskilling strategies for AI implementation in business activities. The initial 82 articles that were downloaded from the aforementioned databases were then reduced to 58 articles following application of exclusion and inclusion criteria. While utilization of the method is appropriate in the research, utilization of the secondary qualitative sources has some limitations, such as potential contextual issues and uncertainty regarding the methodologies employed in some of the included studies. The study also employed thematic analysis, which involves a structured and careful process of identifying recurring ideas, reviewing and interpreting data, to understand different perspectives and providing detailed insights to complex dataset.

Data Analysis

The studies included in this literature review and other relevant and verifiable document comprised the main dataset. Each document was carefully examined to ensure it was directly related to the study's objectives. Relevant details such as conceptual review, theoretical framework, empirical insights, methodologies, challenges and opportunities regarding workforce upskilling strategies and AI integration in business operations were gathered. The process started with a detailed reading of all relevant documents to identify recurring themes, patterns, and key concepts related to workforce upskilling strategies and AI integration in business operations. These identified themes were then categorized and analyzed to address the study's objectives.

Thematic Analysis Findings

Methods of Training and Development (T&D) for AI Adoption in Business Operations

The importance of T&D programs can never be over emphasized as they serve as a strategic leverage to bridge the skill gap, created by the rapid influx of technological innovations (Muchiri, 2022; Li, 2024; Whitehead, 2022). Methods of T&D can be reviewed by classifying them into various dimensions. These dimensions include:

a) Theoretical Foundations and Frameworks

Training and development approaches to AI adoption are taken from proven theoretical models. Technology-Organization-Environment (TOE) and Technology Acceptance Model (TAM) models are most commonly referenced to conceptualize adoption behavior (Shahzadi, Jia, Chen, & John, 2024; Merhi & Harfouche, 2024; Wang et al., 2021). Such models propose that the use of AI or its non-use is not solely a function of a company's choice for its technology but also of organizational preparedness, leadership, and situational factors. Thus, a perception of AI tool's, "usefulness" and "ease of use" by the individual is crucial determinants of the adoption intention, and this drives the strategy that will be most enacted for effective adoption (Wang et al., 2021; Chatterjee, et al., 2021).

b) Traditional vs. Contemporary Training and Development Strategies

There are a number of contemporary T&D strategies which are critical for effective AI adoption. These methods include eLearning, microlearning, virtual reality (VR), personalized learning paths, agile learning, gamification and remote/hybrid training (Zamlynskyi, Camara, Al Ali, & Buzunar,2022; Trifu, Darabont, Ciocîrlea, Ivan,2024). However, best approaches are combinations of conventional and technology-based learning. Although conventional methods such as simulations, role-playing, on the job training (OJT) and group-building (Tang, Nikolaenko, Boerwinkle, Obafisoye, Kumar, Rezayat & Lorenz,2024), continues to work in skills building, its combination with off-the-job approaches like e-learning and workshops has been discovered to enhance worker performance and degrees of creativity (Hussain, 2023; Dixit & Jatav, 2024). The digital age has also brought more trainee-focussed approaches with flexibility and active learning activities (Cunningham, Mergler, & Wattie, 2022). Besides these hybrid approaches, AI also contributes to redefining the training process. With AI tools like ChatGPT, Google Gemni, Perplexity and so on, personalized learning became easier, personalized and self paced.

c) Business Objectives, Structure and Culture

The most effective training methods are those that are strategically aligned to organizational objectives, structure and culture that encourage ongoing learning. The company must also ensure the workers get the tools and knowledge necessary to gain confidence and overcome resistance or fear of new technology (Hasan, Haque, Nishat, & Hossain, 2024; Nurlia et al., 2023; Wang et al., 2021). An organization with a culture of continuous learning imbedded maintains a proactive approach in training and development, which results to increased loyalty and retention (Alrazehi, Amirah, & Emam, 2021).

Table 1: Various Methods of training and development for AI adoption in business operations

S/N	Codes	Theme	Description	References
1	Models	Theoretical Foundations and Frameworks	The Technology-Organization-Environment (TOE) and Technology Acceptance Model (TAM) frameworks are frequently cited for explaining adoption behavior.	Shahzadi et al. 2024; Merhi & Harfouche, 2024; Wang et al., 2021; Chatterjee et al., 2022
2	Traditional VS Digital Age	Modern Training and Development Methods	The digital age has given rise to more trainee-focused methods, providing greater flexibility and active learning opportunities.	Hussain, 2023; Dixit & Jatav, 2024; Chatterjee et al., 2022; Zamlynskyi, Camara, Al Ali, & Buzunar,2022; Trifu, Darabont, Ciocîrlea, Ivan,2024; Tang, Nikolaenko, Boerwinkle, Obafisoye, Kumar, Rezayat & Lorenz,2024
3	Strategic goals, Norma and believes	Business Objective, Structure and Culture	The most successful training programs are those that are strategically aligned with organizational goals and foster a culture of continuous learning.	Hasan et al., 2024; Nurlia et al., 2023; Wang et al., 2021; Alrazehi, et al., 2021).

Source: Researchers compilation, 2025.

Table 1 shows the themes for various methods of training and development for AI adoption in business operations. Embedded in the table are the various codes leading to the themes, description of each theme and relevant citations.

Challenges and opportunities of Re-skilling and Cross-training for AI process reengineering

a) Challenges of Re-skilling and Cross-training for AI process reengineering

AI process reengineering and the associated workforce development strategies face significant challenges. Some of the challenges include;

- High BPR project failure rate: several studies have revealed a high level of failures of BPR projects which are usually as a result of lack of support from senior management, employees resistance to change and in most cases, insufficient funding and lack of access to these technological innovations and infrastructures (Bayomy, Khedr, & Abd-Elmegid, 2021; Hnylianska, 2022; Raffak, Lakhouili, & Mansouri, 2024). In addition, fear of losing one's job position, posses a treats to successful implementation of re-skilling and cross-training initiatives (Gruenewald & Mueller, 2025; Hasan et al., 2024).

- Lack of Longitudinal Studies: There is an observed scarcity of research and information that monitors the efficiency re-skilling and cross-training initiatives (Hajam & John, 2024; Vetrivel & Mohanasundaram, 2024). It is difficult to measure constructs like morale and innovation, since their KPIs are abstract, thus making it difficult to actually ascertain their return on investment (ROI) and long-term impact on the workforce (McEtheran et al., 2024; Muchiri, 2022).

- Geographical Unbalance and Ethical Concerns: Notable and empirical research works are usually carried out in more developed countries than in developing or underdeveloped countries. This makes it difficult to have a conclusive or generalized result (Hajam & John, 2024; Rangarajan and Rubasrce; Hasan et al. (2024).

- Governance and Implementation: Regardless of the efforts that has been made to come up with high level ethical practices and usage of AI, detailed guidelines on reskilling and cross-skilling methods for a successful AI process reengineering are still lacking. There is need to develop systems that mitigates amongst technical AI developers and domain experts (Zamil, Jyoti, & Ikbal, 2023; Hasan et al., 2024). It is necessary to build trust, ensure ethical use in integrating AI into workflows without deteriorating human efforts and abilities (Mahapatra & Dash, 2022; Blezek, Olson-Williams, Missert, & Korfiatis, 2021).

Table 2. Challenges of Re-skilling and Cross-training for AI process reengineering

S/N	Codes	Theme	Description	References
1	Technological innovations and projects	High failure rate for BPR projects.	A high failure rate for BPR projects is often cited, often due to a lack of senior management support, inadequate financial resources, and employee resistance to change.	Bayomy, Khedr, & Abd-Elmegid, 2021; Hnylianska, 2022; Raffak, Lakhouili, & Mansouri, 2024; Gruenewald & Mueller, 2025; Hasan et al., 2024
2	Researches	Lack of Longitudinal Studies	There is a scarcity of long-term studies that track the effectiveness of re-skilling and cross-training beyond short-term interventions.	Hajam & John, 2024; Vetrivel & Mohanasundaram, 2024; McEtheran et al., 2024; Muchiri, 2022
3	Environmental Considerations	Geographical Imbalance and Ethical Concerns	A majority of high-impact studies originate from developed countries, neglecting the unique	Hajam & John, 2024; Rangarajan & Rubasrce, 2024; Hasan et al., 2024

			challenges and contexts of developing economies	
4	Leadership Structures	Implementation and Governance	There is still lack of detailed, practical guidelines for re-skilling and cross skilling in order to enhance AI integration.	Zamil, Jyoti, & Ikbal, 2023; Hasan et al., 2024; Mahapatra & Dash, 2022; Blezek, Olson-Williams, Missert, & Korfiatis, 2021

Source: Researchers compilation, 2025.

Table 2 describes the themes Challenges of Re-skilling and Cross-training for AI process reengineering. The table shows the various codes leading to the themes, description of each theme and relevant citations.

b) Opportunities of Re-skilling and Cross-training for AI process reengineering

Regardless of the challenges AI process reengineering and the associated workforce development strategies may encounter, there exist lots of opportunities. Re-skilling and cross-training are important for leveraging AI reengineering for more improved business processes. Some of the opportunities include;

- Development of a more flexible and effective workforce: The process of AI reengineering, enables development of a workforce that is flexible, effective, efficient and even more productive. Employees are then relieved of repetitive tasks, which allows them to focus on more strategic tasks such as planning, implementing, problem solving and even communication with customers (Khayatbashi et al., 2025; Hnylianska, 2022; Blezek et al., 2021).
- Personalized, adaptive learning and accelerated skill gap analysis: AI tools and reengineering procedures can detect individual learning styles and skill gaps, and then develop personalized, self-paced learning trajectories. This type of learning is also called micro-learning. It is an approach which gives employees access to information and data so they can learn at their own pace and concentrate on their areas of greatest need (Dixit & Jatav, 2024; Nurlia, Daud, & Rosadi, 2023, Ekuma, 2023; Popoola et al., 2024).
- Improved human-AI collaboration: There is usually a noticeable drift in the nature of jobs through AI reengineering processes. AI integration processes can automate routine tasks thereby creating new opportunities for human and AI to work together. Re-skilling focuses on developing greater levels of cognitive skills such as problem identification which in turn solutions are easily mitigated through AI capabilities (Ekuma, 2023; Diaz, 2024; Ledro et al., 2023; Cunnigham et al., 2022).
- Cost-saving Mechanism: Re-skilling and cross-skilling are means through which organizations can save cost and then redirect such finances towards AI reengineering process. Reskilling as a mechanism, allows for employees to move between departments without being laid off, while cross-training gives employees a variety of skills that enhances their flexibility and promotes teamwork. (Muchiri, 2022; Rangarajan & Rubasree, 2024; Hernaus, Černe, & Škerlavaj, 2021; Karder, Beham, Hauder, Altendorfer, & Affenzeller, 2021). If well implemented, these initiatives can motivate these workers, and talents retained, thereby reducing the cost of hiring and training new employees (Copper, 2024; Muchiri, 2022). In addition, motivated workers are efficient and productive

workers, and these attribute in itself help organizations meet objectives at minimal costs (Mirakyan, 2024; Jamal, El Nemar, & Sakka, 2025).

Table 3. Opportunities of Re-skilling and Cross-training for AI process reengineering

S/N	Codes	Theme	Description	References
1	Work Efficiency, Output Quality, Productivity.	Development of a more flexible and effective workforce.	Employees are freed from repetitive tasks to concentrate on strategic thinking, problem-solving, and direct customer interaction as AI automates manual processes like data entry and invoice processing.	(Khayatbashi et al., 2025; Hnylianska, 2022; Blezek et al., 2021).
2	Skill gap, Talent Management, Continuous Learning.	Personalized, adaptive learning and accelerated skill gap analysis.	AI tools and reengineering procedures can detect individual learning styles and skill gaps, and then develop personalized, self-paced learning path ways.	Dixit & Jatav, 2024; Nurlia, Daud, & Rosadi, 2023, Ekuma, 2023; Popoola et al., 2024.
3	Cognitive enhancement	Improved human-AI collaboration	There is usually a noticeable drift in the nature of jobs through AI reengineering processes. AI integration processes can automate routine tasks thereby creating new opportunities for human and AI to work together.	Ekuma, 2023; Diaz, 2024; Ledro et al., 2023; Cunnigham et al., 2022
4	Cost management	Cost-saving Mechanism	Re-skilling and cross-training are key strategies for capitalizing on effective cost saving mechanism in organizations.	Muchiri, 2022; Rangarajan & Rubasree, 2024; Copper, 2024; Hernaus et al., 2021; Karder, et al., 2021; Mirakyan, 2024; Jamal et al., 2025).

Source: Researchers compilation, 2025

Table 3 describes the themes Opportunities of Re-skilling and Cross-training for AI process reengineering. The table shows the various codes leading to the themes, description of each theme and relevant citations.

Discussion of Findings

This study has shown that workforce upskilling strategies are vital towards a successful integration of AI for effective and efficient business processes. The findings from the first theme revealed that strategic training and development programs are key important tools towards AI adoption, and also fosters an organization's readiness for AI integration for business processes (Hussain et al., 2023). Modern training methodologies, including blended learning and the use of AI for personalized and adaptive learning, are essential for making AI more accessible and for overcoming psychological barriers like anxiety and resistance to change (Hasan et al., 2024; Wang et al., 2021). The study also assert that T&D not only improves output quality and productivity, but it also needed in fostering a culture of continuous learning which is pivotal to an organization's ability in maintaining competitiveness and enhancing growth (Muchiri, 2022). This proposes that for business to fully relish on the adverse benefits of AI, they must first invest in a human-centric learning ecosystem that empowers employees to engage with new technologies confidently.

The second theme analyzed potential challenges and opportunities of re-skilling and cross-training for AI process reengineering. Re-skilling and cross-training as upskilling strategies are face with certain obstacles. These challenges are not limited to high failure rate for BPR projects, a lack of senior management cooperation and support, ethical concerns and deep-seated employee fears about job insecurity (Bayomy et al., 2021; Gruenewald & Mueller, 2025). However, opportunities still exist such as that by automating routine tasks, AI process reengineering allows for a fundamental job redesign that shifts the human focus to higher-value, creative work, leading to a more agile and efficient workforce (Khayatbashi et al., 2025; Hnylianska, 2022). Re-skilling and cross-training are the primary enablers of this transition, helping to retain talent, boost morale, and build a flexible workforce capable of adapting to new roles (Copper, 2024; Jamal, El Nemar, & Sakka, 2025).

These findings explain that the successful integration of AI is a complex and multi-faceted challenge that cannot be solved by technology alone, but also through human influences such as interest of all stakeholders in an organization. The pervasive research gaps across both themes such as the lack of longitudinal studies, the geographical imbalance in research, and the difficulty of measuring intangible benefits point to a field that is yet to be explored (Hajam & John, 2024; Vetrivel & Mohanasundaram, 2024). Therefore, researchers need to take steps towards not only technical aspects of AI integration but also on human- centric components which will be focused on creating realistic guidelines, encouraging collaborative cultures and most importantly, practical strategies to resistance from employees.

Conclusion

This study evaluated Workforce upskilling and AI integration for business processes. A qualitative method was used to critically analyze and obtain in-depth insight for the study. Data was sourced from secondary means and analyzed using thematic analysis. The study revealed that the successful adoption and integration of AI is not just a technical endeavor but is solely dependent on the human resources of an organization and the nature of their environment. It also went further to explain that methods for T & D in the context of AI adoption are rooted in theoretical frameworks, a blend of traditional and modern methods, and strategic processes rooted in the culture of the organization. The study also revealed that challenges affecting re-skilling and cross-training for AI reengineering include lack of support from senior management, inadequate financial resources, and employee resistance to change. However, opportunities that exist include creation of more agile and efficient workforce and human-AI collaboration, personalized learning and cost reduction. This study also has some limitations which are relevant for researchers intending to look into areas similar to this study. The adoption of qualitative analysis which is thematic analysis makes it difficult to generalize findings. Methodological and data collection constraints are also evident. Collecting data solely from secondary qualitative source, whose contexts differ from the current environment also limits the study. Therefore, it is advised that intending researchers see to the use of empirical sources such as interview, questionnaire and some secondary quantitative sources.

Limitation

The study is limited by its exclusive reliance on secondary qualitative data, which restricted the ability to obtain context-specific and firsthand information relevant to the phenomenon under investigation. The absence of primary data collection means that the findings are based on previously published materials, which may not fully capture the unique institutional, cultural, or operational realities of the study context. Consequently, the lack of empirical evidence constrains the robustness of the analysis and reduces the extent to which the findings can be generalized to broader populations or settings. This methodological limitation underscores the need for caution in interpreting the results and highlights the importance of incorporating empirical approaches in future studies to enhance validity and generalizability.

Recommendations

Following the findings from this study, it is recommended that:

a) Institutionalize Continuous AI Learning Programs

Businesses should develop structured, continuous learning systems that focus on AI literacy and digital skills. This can include quarterly workshops, AI awareness seminars, and microlearning platforms that enable employees to learn at their own pace. Such programs will help overcome resistance to change and build long-term confidence in using AI tools.

b) Integrate Blended Training and Development Models

Firms should combine traditional methods like on-the-job training and mentoring with modern digital tools such as virtual simulations, e-learning, and AI-assisted personalized modules. This blended approach ensures employees at all levels gain both the technical and soft skills necessary for effective AI adoption in daily operations.

c) Secure Leadership and Financial Commitment for Upskilling

Top management should actively sponsor and champion AI upskilling programs by allocating dedicated budgets, monitoring implementation, and linking skill development to organizational performance metrics. Strong leadership support will reduce project failure rates and ensure employees view AI initiatives as opportunities rather than threats.

d) Implement Strategic Re-skilling and Cross-training for Workforce Agility

Organizations should establish formal re-skilling and cross-training frameworks that rotate employees across departments, helping them develop multi-functional capabilities. This not only lowers recruitment and training costs but also creates a flexible, adaptive workforce capable of collaborating effectively with AI systems for higher productivity.

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