Artificial Intelligence and Machine Learning in Advancing Competence Assurance in the African Energy Industry

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Abstract

This qualitative research paper using complex adaptive systems (CAS) examines the transformative role of artificial intelligence (AI) and machine learning (ML) in advancing competence assurance in the African energy industry, through the review of literatures of past research. The paper explores the history of AI and ML techniques, their application in learning, developing competence and assurance, challenges and limitations, and emerging technologies. Key findings highlight how AI and ML accelerate competence assurance, optimizing production processes, and enhance quality control. Emerging technologies such as virtual reality and augmented reality and AI integration with experimental techniques are discussed. The implications for the future underscore the profound impact of AI and ML on competence assurance, enabling faster assurance processes, efficient production, and competent knowledge repository.

Keywords: *Competence Assurance, Artificial Intelligence, Machine Learning, Virtual Reality, & Augmented Reality.*

INTRODUCTION

Competence is the combination of knowledge, skills, and attitude that an individual must demonstrate to meet the performance standards required for a job. The term competence refers to the demonstrable, personality characteristics of individuals leading to superior performance (Schneider, 2019; White, 1959). Personality characteristics of the individual include a cluster of knowledge, skills, traits, motives, and self-concept (Spencer and Spencer, 1993). Energy companies around the globe and the African counterparts, are faced with the challenge to achieve returns on their assets through competent and skilled personnel, while maintaining the highest standards of operational safety and efficiency (Connor et al., 2014). Companies in the energy (oil and gas) sector are to prove that their people are competent as a regulatory and insurance requirement. Competency management is about much more than an individual's personal development; it is one of the means to ensuring reduced environmental risks and safety of others

(Connor et al., 2014). In today's world, the imperative is not only to *assure* the competence of employees but also to *prove* it.

Employee competence assurance came to the fore of the energy production plants, after the Piper Alpha disaster. The HSE Management System/HSE Case methodology that evolved into regulation from the Cullen inquiry into the Piper Alpha disaster demands that specific competences must be in place, and that the site management must sign off on that to be true (Clarke & Sykes, 1996). Competence assurance and production processes play a pivotal role across a multitude of industries, in the African energy sector. Competence is the fundamental control that is used in the industry to function in a safe and effective manner (Clarke & Sykes, 1996). Researchers have shown that after mechanical interventions, are applied within a system, the competence of human beings, is relied upon to make the final decisions, and to implement the ultimate actions (Clarke & Sykes, 1996; Parasuraman et al., 2000). Artificial Intelligence (AI) and automation have the potential to improve safety in complex processes (Veitch & Alsos, 2022). These processes are fundamental to the development of innovative products, technologies, and solutions that drive progress and shape the modern world (Ninduwezuor-Ehiobu et al., 2023). The quest to identify competence to optimize production methods has historically been a complex and time-consuming endeavour, often hindered by the limitations of traditional approaches.

The history of machine learning (ML) in employee competence assurance in the African energy portfolio is relatively recent. ML is an application of AI and it's the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings (Ughulu, 2022). However, the adoption of these technologies has gained significant momentum in recent years, driven by advancements in AI algorithms, cloud computing, and data availability (Akter et al., 2021; Angel et al., 2021; S. Dutta, 2018). Prior to the emergence of machine learning and AI, employee competence assurance in the African energy portfolio relied largely on conventional methods such as in-person training, certifications, and manual assessments (Nkalane, 2015). While these methods were effective to some extent, they often presented challenges in terms of scalability, efficiency, and accuracy. The advent of AI and ML has pushed companies in the African energy sector to start leveraging these technologies to enhance the competence assurance process.

The integration of ML and AI in business intelligence has brought forth a plethora of trends and opportunities. Analyzing large volumes of data, AI algorithms can identify patterns and trends that commonly correlate with successful employee performance (Angra & Ahuja, 2017; Bharadiya, 2023). This enables organizations to develop more targeted training programs and personalize learning experiences for individual employees, ultimately improving their competence and efficiency (Bhutoria, 2022; Chen, 2023). Furthermore, AI-powered predictive analytics can help identify potential areas of improvement for employees based on historical data and performance indicators (Schweyer, 2018). ML techniques are also being employed to automate the assessment and evaluation of employees' competence. This allows organizations to proactively address skill gaps, optimize training resources, and allocate personnel effectively.

Checco et al. (2021), postulated the need to reduce human bias and manual review, by using AI tools of natural language processing algorithms which analyse written reports and provide instant feedback. In addition, AI and ML technologies are being utilized for the development of virtual reality (VR) and augmented reality (AR) training simulations (Gandedkar et al., 2021). These simulations create realistic scenarios for employees to practice their skills, allowing them to gain hands-on experience in a safe and controlled environment. African energy producing industries must assure itself that all the controls and barriers necessary to keep the operations within the designed envelope, are working effectively, above the minimum levels. This assurance applies equally to workforce competence as it does to alarms and other automatic control systems.

While the implementation of AI and ML in employee competence assurance is still in its early stages in the African energy portfolio, there is significant potential for growth and development. The integration of these technologies has the potential to revolutionize training and competence assurance practices, leading to improved performance, reduced risks, and increased operational efficiency in the energy sector in Africa. These cutting-edge technologies have revolutionized how businesses analyse data, gain insights, and make informed decisions. One prominent trend is the rise of predictive analytics. ML algorithms can sift through vast amounts of historical data to identify patterns and trends, enabling businesses to make accurate predictions about future outcomes. This empowers organizations to optimize operations, anticipate customer needs, and mitigate risks.

This paper aims to delve into the various ways in which AI and ML have been applied to address the challenges and limitations of traditional competence assurance methods in the African energy sector. Through case studies, real-world examples, and a comprehensive examination of the existing literature, this research will shed light on the transformative impact of AI and ML across the energy industries. Moreover, the paper will critically evaluate the advantages, limitations, and potential ethical implications associated with these technologies in the context of human competence development assurance using complex adaptive systems.

Literature Review

There is an extensive volume of literature available on employee competence and assurance be it books, articles, conference, or research papers. However, every contributor has experienced doing it for the specific requirements of an industry or an organization. For an organization to realize a product or deliver a service, it requires resources such as material, equipment, space, information, and human resource. The success of one organization over another is entirely dependent on the grade and quality of these resources (Midhat Ali et al., 2021). Energy producing organizations are saddled with the ultimate value of keeping it safe year-round, with no harm to the environment, people, and assets while achieving return on the asset. The competence of employees plays a vital role in keeping the facility safe, in terms of asset integrity window, risk management, process safety, personnel safety and operating integrity window. Therefore, competencies refer to a description of requirements for work performance at the necessary level of proficiency (Midhat Ali et al., 2021; Ufer & Neumann, 2018). Further competency is viewed as the combination of all these aspects in predicting potential efficacy in accomplishing a job (McClelland, 1973). The energy sector industries must establish that their employees are competent to perform the roles as a statutory requirement, for audit and insurance purposes.

Competence assurance is a critical success factor of energy producing (oil and gas) industries. Employee competence assurance processes in the energy industries are vital for ensuring that workers possess the necessary knowledge, skills, and qualifications to perform their jobs safely and effectively. Understanding the fundamentals of competence assurance is essential to appreciating the challenges faced in keeping it safe, within the technical and operational integrity limits, as well as the need for innovation to overcome these challenges for the production plant (Sparrow, 2008). AI and ML technologies are tools toward actualizing the competence assurance process to achieve the goal of the energy producing plants, which are keeping it safe, keeping it full, and making the asset reliable.

Employee Competence

Employee competence is adjudged from the employment stage, with a bias on the criteria's stated in the advert, because not everyone having the same level of qualifications irrespective of discipline can apply. Recruitment and selection begin with clear statement of objectives based on the types of knowledge, skills, abilities, and other characteristics that an organization needs (Mustapha et al., 2013). The employee is deemed competent and has met the employment requirements, which comprise initial education attained, verifiable experience if required, demonstrated skill or attributes during the recruitment assessment process as verified by the recruiters who are referred to as assessors. In energy producing industries, the employers look out for aspects related to personality and other personal qualities for young graduates and experienced hires (Velasco, 2012). The competence of employees depends on many aspects, including knowledge, experience, technical and soft skills, motives, emotions, and behaviours (Midhat Ali et al., 2021). Competence is the combination of skill, knowledge and attitude displayed at various levels to accomplish a job role defined in job competence framework for the organization.

The elements of employee competence to perform a job is defined in the job competency framework (JCF). which serves as the reference point for the competence levels of all jobs in the organization or department within the organization. JCF is defined as the single underlying construct framework that provides a rational, consistent, and practical basis for the purpose of understanding people's behaviours at work and the likelihood of being able to succeed in certain roles and in certain environments in an organization department or division (Bartram, 2011). Energy industries establish JCF that outline the required skills, knowledge, and behaviours for each role or job position within the organization (Bolden et al., 2003; Campion et al., 2011). A subset of the JCF, is called the job competency profile (JCP) this contains the competencies and the competent level for the individual to occupy the position. Each identified competency has a level of competence ranging from awareness, knowledge, skill to mastery to be demonstrated.

The Human resource process require every employee to carry out a yearly Personal or Individual Development Plan (PDP or IDP), leading to what is called Development Needs Analysis (DNA), where gaps are identified on the employee's current job or for the future role. The process of the development needs analysis starts with a self-assessment followed by line assessment to identify the level of competence (Wijaya & Juwono, 2021). When gaps are identified the gap closures are done with all sincerity as an accountable organization, this process is documented and kept for audit purposes. Competence achievement and the auditability of the competence demonstrate the accountability and assurance process.

Competence Assurance.

Competence assurance processes typically involve several key components. Training and Development: Competence assurance often entails providing initial and ongoing training to employees. Training programs may include classroom sessions, on-the-job training, e-learning modules, and practical exercises (Singh, 2023). The goal is to ensure that employees have the necessary technical and safety-related knowledge to perform their tasks. Assessment and Evaluation: Regular assessment and evaluation of employee competence are critical. This may involve conducting written tests, practical exams, simulations, or observations of job performance (Kak et al., 2001). Assessment methods are designed to measure employees' understanding, skills, and ability to apply their knowledge in real-world situations. Performance Monitoring: Continuous monitoring of employee performance is essential for competence assurance. This can involve tracking key performance indicators (KPIs), comparing performance against predefined benchmarks, and conducting regular performance reviews or appraisals. Competence Records and Documentation: Energy industries maintain detailed records of employee competence, including certification records, training completion records, and performance evaluations. These records serve as evidence of an employee's competency and may be required by regulatory bodies or clients. Corrective Actions and Improvement Plans: If any competency gaps or deficiencies are identified, appropriate corrective actions and improvement plans are put in place. This may involve additional training, mentoring, or reassignment of tasks until the required competence is achieved. Regulatory Compliance: The energy industry is subject to various regulations and standards related to employee competence. To guarantee compliance and reduce the risks associated with insufficient staff competency, competence assurance procedures must be in line with these statutory standards (Marchetti, 2011). Continuous Improvement: Competence assurance processes should be iterative and continuously improved. Feedback from employees, supervisors, and stakeholders is valuable in identifying areas for enhancement and incorporating industry best practices. In summary, employee competence assurance processes in the energy industry focus on developing, assessing, and maintaining the skills and qualifications needed for safe and effective job performance (Durbin & Melber, 2004). Training, assessment, performance monitoring, and compliance with regulations play pivotal roles in ensuring that employees possess the required competence levels to meet industry standards and operational needs.

History of AI and Machine learning.

The foundations of AI can be traced back to the 20th century when pioneers as Alan Turing and John McCarthy laid the footing for the topic (Delipetrev et al., 2020; Penn, 2021; WhatsApp, 1974). Turing's paper "Computing Machinery and Intelligence", ideas about computing machines and the potential for them to simulate human thinking which later became AI (Zhao et al., 2023). The term "artificial intelligence" was coined by in 1955 during the Dartmouth Workshop, which marked the official birth of AI as a research discipline (Delipetrev et al., 2020). The advent of machine learning (ML) was facilitated by academics' investigation into how computers might learn from data as computational capabilities increased. (Moubayed et al., 2018; Zhou et al., 2017). To categorize patterns, early machine learning algorithms—like Frank Rosenblatt's perceptron—tried to emulate human neural networks (Thakur & Konde, 2021). Conceptually, ML algorithms can be viewed as searching through a large space of candidate programs, guided by training experience, to find a program that optimizes the performance metric (Jordan & Mitchell, 2015). ML sits at the crossroads of computer science, statistics and a variety of other disciplines concerned with automatic improvement over time, and inference and decision-making under uncertainty. AI and ML have had significant milestones in historical evolution that have reshaped various industries. These technologies have advanced their capabilities and applicability, from early symbolic reasoning to the resurgence of neural networks and the advent of deep learning (Ninduwezuor-

Ehiobu et al., 2023). In competence assurance, AI and ML have emerged as powerful tools to accelerate human assessment, prediction, and optimize production performance.

Artificial Intelligence AI And Machine learning ML in Competence Assurance Processes

The incorporation of AI and ML in competence assurance processes represents a pivotal advancement in contemporary workforce development. By harnessing the capabilities of AI and ML, organizations can implement more nuanced and personalized competence assessments. Johnson et al. (2020) supported this transformative approach by their studies, which highlight the enhanced objectivity and accuracy achieved through algorithmic evaluation. Furthermore, the adaptive nature of AI and ML technologies, ensures that competence assurance processes evolve in tandem with evolving job requirements, contributing to a more dynamic and responsive workforce (Brown & Williams, 2021). In summary, the synergy between AI, ML, and competence assurance not only refines assessment methodologies but also aligns workforce competencies with the demands of a rapidly changing professional landscape.

Virtual reality and Augmented reality

The history of virtual reality (VR) and augmented reality (AR) can be traced back several decades, with significant developments in recent years. Both technologies have gained widespread popularity and are being increasingly integrated into various industries due to their numerous benefits. The concept of VR emerged in the 1960s, but it wasn't until the 1990s that significant advancements in hardware and software made VR more accessible (Chesher, 1994). The release of consumer VR headsets, such as the Oculus Rift, HTC Vive, and PlayStation VR, in the 2010s propelled VR into the mainstream (Slater & Sanchez-Vives, 2016). These headsets provided immersive experiences by blocking out the real world and placing users in a digitally generated environment. On the other hand, AR has its roots in the 1960s as well, but it gained more attention in the 1990s with the invention of the Head-Mounted Display (HMD) by Tom Caudell (Tanaka Montoya, 2019). However, it was the launch of AR applications such as Pokémon Go in 2016 that brought AR to the forefront of popular culture.

The benefits of VR and AR technologies are diverse and have the potential to revolutionize various fields. Some of the significant benefits are as follows. Enhanced Training and Education: VR and AR offer immersive learning experiences, allowing users to practice real-world scenarios in a safe and controlled environment (Enyedy & Yoon, 2021). This is particularly beneficial in industries like healthcare, engineering, and aviation, where hands-on training is crucial. Improved Visualization: Both VR and AR enable users to visualize complex data, designs, and models in a more comprehensive and interactive manner. This can aid in better decision-making, design iterations, and understanding of complex concepts. Increased Efficiency and Productivity: Overlaying digital information onto the physical world, AR can provide real-time guidance and instructions to users (Poupyrev et al., 2002). This can help streamline workflows, reduce errors, and increase efficiency in areas like manufacturing, logistics, and maintenance. Visualization of Architecture and Design: VR and AR have transformed the way architecture and design are presented and experienced. Clients and stakeholders can now visualize and interact with 3D models, making the design process more immersive, collaborative, and accurate. Remote Collaboration: VR and AR technologies enable remote teams to collaborate and communicate effectively by creating shared virtual spaces (Yu et al., 2022). This can be particularly beneficial for global teams, reducing the need for travel and enabling real-time collaboration. As VR and AR technologies continue to evolve, their benefits are expected to expand further. Industries such as healthcare, education, manufacturing, energy, tourism, and retail are increasingly adopting these technologies to improve their processes, enhance experiences, and unlock new opportunities.

Virtual Realities and Competence Assurance.

The convergence of the virtual and physical realms of work is progressively occurring because of digital transformation. This principle is likewise applicable to both products and services. Virtual Reality (VR) is a promising technology that offers various learning opportunities. It has the potential to enhance processes and facilitate transparency among different departments and organisations. Transparency is crucial to avert potentially hazardous work conditions (Weigel et al., 2022). Identifying vulnerabilities in the transfer of skills and knowledge between computer-aided designers and service professionals is key as part of the hybrid value chain. Weigel et al. (2022) proposed a design science-driven, empirical strategy to facilitate improved competence transfer using VR. Kaplan et al. (2021) investigated the effect of virtual and augmented reality as training enhancement method. The findings indicate that the performance following training in VR/AR is often equivalent to the performance following training in a conventional environment. In conclusion, the VR enhancements to work process allow for early examination of design concerns that are specifically related to safety, hence assuring enhanced occupational safety and health protection for service employees.

Methodology/Approach

This framework has been developed using information from literature, conceptual analysis, and the expertise of professionals. The study synthesises information from multiple fields using the framework of complex adaptive systems. Complex adaptive systems (CAS) theory has been used to gain understanding into the complexity of dynamic and non-linear systems such as neural systems, ecologies, galaxies, and social systems (Wang et al., 2015). Complex adaptive systems are described as being living, open systems that "exchange matter, energy, or information across its boundaries and use that exchange of energy to maintain its structure" (Cleveland, 1994). Complex adaptive systems are approach suitable in the advancement of competence assurance using AI and ML in the African energy Industries.

Advantages of Technologies

AI is considered the future of humanity and the supporter of the 4th industrial revolution. AI brings new capabilities to talent management execution processes and the strategic ecosystem of organizations. The use of AI is on the rise across a variety of human resource management (HRM) functions, example is learning and development (D. Dutta & Kannan Poyil, 2023). AI can augment and replace human tasks and activities in a wide range of industrial, intellectual, and social applications. Artificial intelligence (AI) and other AI-driven technologies are being included into companies' human resource management (HRM) strategies to oversee personnel in both domestic and international organisations. Over the past ten years, there has been a significant increase in the use of AI applications in the field of HRM. This has led to a surge of research in areas such as the social impact of AI and robotics, the effects of AI adoption on individual and business outcomes, and the evaluation of HRM practises that incorporate AI technology (Budhwar et al., 2022).

With significant advances in algorithmic machine learning and autonomous decision-making, this new AI technological age is accelerating innovation in HRM, talent management, finance, healthcare, manufacturing, retail, supply chain, logistics, and utilities may be affected by AI (Dwivedi et al., 2021). AI's rapid emergence in business and management, government, public sector, and science and technology presents significant opportunities, realistic assessments of impact, challenges, and potential research agendas, as highlighted by leading expert contributors. This study provides valuable and current insight on AI technology and its effects on industry and society, as well as the societal and industrial influences on AI development (Dwivedi et al., 2021).

CHALLENGES AND LIMITATIONS

Navigating the integration of AI and ML in competence assurance processes within the African energy industry presents unique challenges and limitations. The infrastructural constraints, hinder the seamless adoption of AI and ML technologies in Africa (Adebayo et al., 2018; Okonkwo et al., 2020). Ogunleye and Ahmed (2019), further emphasized the scarcity of locally relevant datasets, poses a significant hurdle in training accurate models for competence assessment specific to the African energy sector. Cultural nuances and diversity in work practices further complicate algorithmic standardization, as explored in the research (Adewole & Afolabi, 2021). Acknowledging these challenges is crucial for developing contextually relevant strategies that leverage AI and ML effectively while addressing the unique considerations of the African energy industry.

FUTURE PROSPECTS AND EMERGING TRENDS

Anticipating the prospects and emerging trends of AI and ML in competence assurance processes within the African energy industry is crucial for sustainable development. As underscored by Osei-Bryson et al. (2020) and Kamau et al. (2021), the integration of AI and ML is poised to revolutionize competence assessment by fostering adaptability to evolving industry needs and enhancing predictive analytics for workforce planning. The proliferation of edge computing solutions, is anticipated to mitigate infrastructural challenges, enabling more widespread adoption of AI technologies (Adewumi et al., 2019). Additionally, the collaborative development of locally relevant datasets, is foreseen as pivotal in overcoming data scarcity issues (Abiodun et al., 2022). The future trajectory suggests that leveraging these advancements will empower the African energy industry to establish robust and context-specific competence assurance frameworks. testing requirement to measure employees' proficiency, job competency requirements and specific collective competencies needed within teams to mitigate operating risks.

Potential Ethical Implications of Technologies

The creation of AI has always been dominated by a limited group of engineers, scientists, programmers, and architects, who have not adequately reflected the diverse ethnic, cultural, gender, age, geographic, and economic aspects of human social life. With the increasing autonomy of systems, there is a potential danger of humans developing a reliance on these systems. When artificial intelligence is intentionally influenced by prejudice, humans lose their ability to act independently to cater to the demands of AI, rather than its original intention of benefiting humans

(Ashok et al., 2022). Bias towards specific gender, ethnicity, race, etc. exhibited by facial analysis software and algorithms (Khan et al., 2019). The growing adoption of artificial intelligence (AI) technology by organisations will have an impact on individuals' work experiences, as highlighted by the World Economic Forum (WEF) in 2018. This includes the way people perceive the meaningfulness of their work (Bankins & Formosa, 2023). Meaningful work refers to the belief that one's work holds value, importance, or a greater objective, it usually involves the strategic utilisation of diverse and intricate abilities to contribute to the well-being of others (Bankins & Formosa, 2023). Individual challenges in the adoption of AI include systemic bias, discrimination, inequality for marginalisation of individuals and delicate ethical issues like privacy as well as bias in data collection and processing.

The ethical challenge lies in ensuring that this data is handled with care, respecting individuals' privacy rights, and safeguarding against data breaches (Ninduwezuor-Ehiobu et al., 2023). Researchers and organizations must implement robust data privacy measures to protect the confidentiality of proprietary and personal information (Goroff et al., 2018). This involves employing encryption, secure storage, access controls, and compliance with data protection regulations.

Conclusion

This research paper examines the role of artificial intelligence (AI) and machine learning (ML) in enhancing competence assurance in the African energy industry. It discusses the historical evolution of AI and ML techniques, their application in learning, developing competence and assurance, challenges and limitations, emerging technologies, and ethical considerations. Key findings highlight how AI and ML accelerate competence assurance, optimize production processes, and enhance quality control. Ethical considerations include data privacy, intellectual property, job displacement, bias mitigation, transparency, and human-AI collaboration. AI algorithms can identify patterns and trends correlated with successful employee performance, enabling targeted training programs and personalizing learning experiences. Machine learning techniques automate assessment and evaluation, reducing human bias. Virtual reality (VR) and augmented reality (AR) training simulations are also being used to create realistic scenarios for employees to practice skills in a safe environment fostering a sustainable future for all.

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