

ARTICLE

## Learning AI System Skills to lead Organisation Systems

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### Abstract

**Purpose:** The present study aims to identify and clarify the key skills related to Artificial Intelligence (AI) systems that organisations must learn to effectively implement AI technology for both current needs and future development.

**Design/Methodology/Approach:** This study reviews literature on learning AI skills and on studies illustrating AI systems. It is organised into two main themes: the application of AI system skills across different sectors, and the impact of AI systems on the future of organisations.

**Findings:** This paper is focused on the new skills and technology of AI systems that are adopted by different organisations to advance the next step in technology. Also, the study focused on the future of these AI systems and the impact of implementing these skills in their organisations.

**Originality:** This paper is a view on AI systems' skills to be learned for the development of organisations in future technology.

**Keywords:** AI Systems; Organisation; Skills; Technology; Learning

### 1. INTRODUCTION

The conversation about technology is fast shifting from what AI (Artificial Intelligence) can do to how organisations and professionals must adapt to it. More importantly, the skills and competencies that will matter in an increasingly automated AI-driven world would lead the organisation into an advanced step [3]. But the insight point is that where technology evolves fast, human expertise would remain central. Based on this, a viewpoint on the skills of AI systems that the organisations are learning to implement is a leap to the current scenario.

### 2. REVIEW LITERATURE

The workplace of the not-too-distant future may be very different from what we have seen today, given the remarkable success of recently launched large language models (LLMs) like ChatGPT. Perhaps the most astounding result of the present data-driven revolution, which is mostly driven by the quick development of artificial intelligence (AI), is LLMs. AI is no longer an option for businesses; it is a crucial strategic tool that can help them better understand and anticipate their customers' needs, develop cutting-edge goods and services, boost operational performance and productivity, and unlock business value [12,13]. The issue is made worse by the growing skills gap [7] and the unequal rates of creation and consumption of AI-related technologies [11], which impede businesses' efforts to obtain useful insights that provide economic value. However, the degree of alignment between the workforce and organisational structure (such as business processes) determines an organisation's capacity to fully utilise AI's huge potential [2]. Retraining current personnel in new technologies like artificial intelligence is an essential component of this workforce alignment [10]. Workforce skills are lagging behind AI investments, according to a recent study of C-suite executives [15]. Additionally, most workers seek increased options for job advancement through AI-related training [10]. Workforce skills are lagging behind AI investments, according to a recent study of C-suite executives [15]. Additionally, most workers seek increased options for job advancement through AI-related training [10]. It is costly and time-consuming to train personnel in new technology, and many business executives anticipate that their staff will pick up new skills on the job [16]. However, AI comprises a wide range of algorithms

that are difficult to master and use in the workplace, and it necessitates a solid background in statistics and programming. How to teach AI skills in an academic setting has been the subject of case studies and existing literature [1,14,17]; The particular difficulties of training high-performing workers on the job, however, are rarely studied [5]. The goal of business executives is always to increase the economic worth of their companies; there must be a compelling reason to take away valuable employee work time for training and education. Therefore, a return on training expenditure would encourage managers to give reskilling people top priority in a commercial setting. Additionally, employees have not been in a classroom setting for many years—in some cases, decades—in contrast to a university setting. This presents special difficulties. The lightweight (i.e., short-term) learning and development method that businesses typically use for reskilling may not be appropriate for complex and transformational subjects like artificial intelligence.

However, many people may not think it is feasible to expect busy and productive workers to take time off to attend a university in order to learn new concepts. Universities often train students for entry-level jobs, leaving the learning and development divisions of businesses to reskill productive workers. The need to retrain the current workforce has grown due to the quick obsolescence of information technologies [10]. Academic institutions now have a chance, but they will need to apply a different pedagogical approach than what is used to instruct regular students. In light of this, we examine the following study question: How can we successfully introduce revolutionary new technologies like AI/ML to the workforce? It first illustrates how an experiential learning strategy that adheres to the learn-apply-reflect cycle speeds up the acquisition and reinforcement of AI/ML ideas and skills and helps staff members comprehend when and under what circumstances they can be applied. Second, both scholars and practitioners can benefit greatly from the case study's main lessons. To better understand what firms need to do to reskill their personnel and recreate themselves digitally, academic staff members might explore a number of difficulties that are revealed by the lessons learned. Additionally, practitioners can utilise these lessons to direct their efforts in encouraging an organisation-wide culture that is driven by data. Lastly, as the trained staff members communicated what they had learned with other staff members, an unexpected but desired result was the spread of a digital attitude throughout the company.

The significance of educating and preparing students for the future in university settings is emphasised in earlier research on learning new AI/ML skills. For instance, Shi et al. [14] highlights a new report-oriented teaching approach for business intelligence courses; Zhang et al. [17] investigates how to train technical and non-technical students in data mining; and Bačić et al. [1] describes their experience creating a graduate certification in data analytics. While ElSayary [5] looks into the effects of increasing teachers' digital competency, Liu and Murphy [8] provides a way to train graduate students in both soft and technical abilities.

Acquiring knowledge of AI/ML is difficult. AI/ML is a multidisciplinary discipline with roots in computer science (particularly, programming and algorithms), statistics and probability, mathematics (e.g., linear algebra), and computational linguistics (e.g., natural language processing, or NLP) [9]. Data pre-processing, feature engineering, model development, and evaluation are just a few of the many ideas that need to be understood. We have found that homework assignments and classroom instruction are insufficient to give students the breadth of knowledge needed to become data scientists. Moreover, mastering the algorithms that underpin supervised, unsupervised, and reinforcement learning approaches is insufficient. Additionally, the students must be able to recognise issues amenable to AI/ML. Another difficult issue is formulating problems, as students rely more on their prior knowledge and approaches to problem-solving.

### **3. AI SYSTEMS SKILLS [6]**

#### **3.1. Enterprise OS**

With voice acting as the main interface for enterprises, native voice operating systems (OS) are currently becoming more popular. Returning to the previous AI transactional period, in which an agent just places a call. The era of the intelligence loop, however, is about to start. The contextual data gathered from every conversation will then be sent to the system. Because of this, voice artificial intelligence systems will be able to instantly increase their intelligence based on actual user behaviour. It will conduct financial audits, automate intricate supply chain logistics, and manage human resources lifecycle events. We may expect forward-thinking organisations to move up to 50% of their total call volumes to voice AI agents as trust in their accuracy grows. Three particular abilities will be essential for success in this field: Understanding how to organise voice interaction data to enhance agent learning models, developing the capacity to lower computation and latency costs as call volumes reach

millions, and developing non-linear conversation flows that maintain emotional nuance and a human-like connection.

### **3.2. AI Systems in Healthcare**

The transition from AI as a feature to AI as an intelligent, clinician-supervised system that supports healthcare quality and consistency will be the most significant change in health technology. The objective is to minimise needless variance and operational difficulties rather than to replace clinical judgment, allowing clinicians to concentrate on what only humans are capable of: making complex decisions, showing empathy, and building trust. When properly structured, autonomy can assist in providing consistent care even in high-volume or resource-constrained training situations, speed up diagnosis times, and allow for more individualised therapy. Professionals will require a T-shaped skill set to succeed in this field. This implies that they need breadth across clinical processes, safety, and validation in addition to expertise in a single field, such as AI/ML, software engineering, imaging, cybersecurity, or data.

### **3.3. AI Systems in the Retail Sector**

Intelligent outcomes will characterise retailing instead of transactions. The future of commerce is not about technology alone; it is about building an intelligent, inclusive and outcome-driven ecosystem for the digital-first generation. This is a major change in the way merchants assess technology: they are now demanding quantifiable business effect, more conversions, lower churn, optimised processes, and sustainable profitability rather than buying software for its novelty. AI is becoming the unseen COO, coordinating resilient supply chains, autonomous pricing, and predictive forecasting. AI is discreetly driving real-time choices about pricing, promotions, inventory, and demand planning, transforming what was previously limited to test projects into mission-critical infrastructure. Brands that modernise their foundations and integrate store data, marketplace logic, supply chain signals, and consumer identities into a cohesive ecosystem capable of real-time adaptation, learning, and action will triumph.

## **4. FUTURE WITH AI SYSTEMS [4]**

### **4.1. AI System Skills are a Connective Tissue**

Organisations will undergo a profound transformation to become really intelligent businesses. AI agents won't merely operate in silos here. They will function as a connecting tissue, reacting to actual situations in a dynamic manner. For instance, in supply chain management, these agents are capable of real-time financial forecast recalibration, alternative sourcing, and disruption detection without the need for human interaction. With the secure, high-performance backbone of cloud infrastructure, the nation's strong digital public infrastructure and cloud maturity offer the perfect environment for this transition. A workforce of systems architects—professionals who combine in-depth domain knowledge with the contextual AI literacy required to guide autonomous agents—replaces the current one of operators. The most resilient companies will be those that enable their employees to coordinate these digital teammates, striking a balance between automated accuracy and the human judgment and critical thinking needed to handle real-world complexities at scale. These agents serve as the enterprise's connective tissue.

### **4.2. AI Will Become Your Co-Worker**

The most significant changes will be the evolution of AI from a useful assistant to a real digital coworker. Businesses will trust autonomous agents to handle end-to-end tasks, collaborate with human teams, and be held accountable for actual business results rather than relying just on AI for analytics or automation. Healthcare and large-scale service settings, where businesses deal with enormous volumes, intricate procedures, and a continuous need for efficiency, will see this shift. In this case, agentic AI will be necessary to expand without increasing operational complexity, not just a nice-to-have. It won't be the most sophisticated models that set a company apart; rather, it will be the ability to successfully integrate AI throughout the entire organisation.

### **4.3. AI Systems' Ability to Frame Problems and Interpret Outcomes**

AI tools will help more thoroughly across the lifespan, but their influence will come from developing the capacity to properly frame issues, critically analyse results, and make well-informed trade-offs rather than from being proficient with any one technology. Every choice will be based on sustainability at the same time.

#### **4.4. Business Data Mining Fundamentals**

With an emphasis on finding and characterising structural patterns in data, this course presents machine learning and statistical methods for useful data mining. Important subjects include methods for association rule mining, classification, clustering, and data preprocessing, cleaning, reduction, transformation, and visualisation.

#### **4.5. Advanced Analytics Techniques**

Advanced statistical inference methods designed for business analytics are covered in this course. This course equips students with the skills necessary to generate and analyse predictive analytics, use statistical data, and successfully use evidence-based decision-making in managerial settings. Confidence intervals, statistical distributions, probability, and hypothesis testing are among the subjects covered.

#### **4.6. Machine Learning/Data Science**

This course offers a thorough examination of Python-based machine learning, feature engineering, and data pre-processing. Supervised machine learning methods, including K-Nearest Neighbours (KNN), Linear, Ridge, and Lasso Regression, Logistic Regression, Bayesian, Decision Trees, Ensembles (such as bagging and boosting), support vector machines (SVM), and Artificial Neural Networks, are important subjects. Natural language processing (NLP) approaches, including topic modelling, named entity recognition (NER), classification (e.g., false news detection) with explainability, and clustering of unstructured text, are also discussed. Lastly, students learn how to interpret complicated unlabelled data using unsupervised methods like K-Means, hierarchical clustering, DBSCAN/HDBSCAN, and t-SNE.

#### **4.7. Big Data Analytics**

Using well-known frameworks like Tensorflow and PyTorch, this course focuses on deep learning algorithms and advanced machine learning approaches. Sequential and functional models, convolutional neural networks (CNNs), recurrent neural networks (RNNs), long-short term memory (LSTM), transformers, autoencoders, and generative adversarial networks (GANs) are among the deep learning models and architectures on which students receive practical training. Large Language Models (LLMs) were developed using advanced NLP approaches, which are also discussed. Homework assignments were created especially for Ericsson using problem statements and datasets that the firm supplied in order to increase the program's relevance and applicability. This strategy made sure that students could use their newly learned abilities to directly address Ericsson's actual business problems. Additionally, in cooperation with Ericsson, the assignments were evaluated and updated on a regular basis. to continue being relevant and in line with changing business requirements.

#### **4.8. Quantum Tech**

Applications with quantum advantages are anticipated to appear shortly, and quantum systems are currently reaching a critical turning point known as the utility-scale. In early application areas, advances in hardware and software will provide us with a clear edge over classical computing, enabling users to execute algorithms that get us closer to the advantages of practical quantum computing. This advancement will come from a network of businesses, academic institutions, research facilities, and start-ups developing algorithms that make use of hybrid classical-quantum processes rather than from a single innovation or organisation. In this manner, the technology will transition from research settings to practical applications. The quantum advantage in certain fields, such as materials research, chemistry, optimisation, and complicated simulations, where classical systems have difficulty scaling. Additionally, we show how the convergence of AI with quantum computing will enable businesses to leverage the advantages of both paradigms in a new high-performance computing architecture. Quantum requires a diverse base in terms of skill.

#### **4.9. Chiplet**

By supporting open chiplet standards, sponsoring pilot-to-production lines, scaling expertise, and linking incentives to power and related performance by carbon intensity, organisations can take the lead. competent experts in 2.5D/3D integration and hybrid bonding, power-thermal co-design, materials and dependability, EDA, high-speed signalling, metrology and yield, including know-good-die testing, and statistical process control (SPC) and equipment automation.

## 5. LIMITATIONS

The study only includes the discussion and examines the approaches of different sectors towards the AI skills system. The study does not support and fails to explain the concept with the help of empirical data. Though the study presents a conclusion based on experts' opinions through secondary review and other secondary sources, it does not express any direct opinion, thereby introducing bias regarding the AI skills system. Therefore, there is a need to work on the primary data source to reduce these biases and bring clarity across broader aspects. Also, there is a need to explain and cover a larger number of sectors/industries to understand the AI skill system.

## 6. CONCLUSION

Strong governance becomes essential when integrating several artificial intelligence (AI) into past systems, multilingual workflows, and regulated environments. AI systems will be built with ethical safeguards, transparency, and real-time monitoring from the start rather than being added after the fact. AI readiness from a talent perspective will rely on emerging hybrid skill sets. Positions like the incorporation of AI architects, LLM operations specialists, and AI governance leaders will become more in demand.

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## REFERENCES

1. Bačić, D., Jukić, N., Malliaris, M., Nestorov, S., & Varma, A. (2023). Building a business data analytics graduate certificate. *Journal of Information Systems Education*, 34(2), 216–230.
2. Besson, P., & Rowe, F. (2012). Strategising information systems-enabled organisational transformation: A transdisciplinary review and new directions. *Journal of Strategic Information Systems*, 21(2), 103–124. <https://doi.org/10.1016/j.jsis.2012.05.001>
3. Bhatt, P., & Muduli, A. (2023). Artificial intelligence in learning and development: A systematic literature review. *European Journal of Training and Development*, 47(7–8), 677–694. <https://doi.org/10.1108/EJTD-09-2021-0143>
4. Bukartaite, R., & Hooper, D. (2023). Automation, artificial intelligence and future skills needs: An Irish perspective. *European Journal of Training and Development*, 47(10), 163–185. <https://doi.org/10.1108/EJTD-03-2023-0045>
5. ElSayary, A. (2023). The impact of a professional upskilling training programme on developing teachers' digital competence. *Journal of Computer Assisted Learning*, 39(4), 1154–1166. <https://doi.org/10.1111/jcal.12788>
6. From tools to systems: Techs next leap. (2025, December 31). *Times of India*, 22. <https://epaper.indiatimes.com/timesepaper/publication-the-times-of-india.city-angalore.cms>
7. Horn, M. B. (2020). Education, disrupted. *MIT Sloan Management Review*, 61(2), 1–5.
8. Liu, X., & Murphy, D. (2021). “BILT for success”: An alternative education strategy to reskill the business and technology professionals for a sustainable future. *Information Systems Education Journal*, 19(2), 4–14.
9. Mike, K., Kimelfeld, B., & Hazzan, O. (2023). The birth of a new discipline: Data science education. *Harvard Data Science Review*, 5(4), 1–26. <https://doi.org/10.1162/99608f92.280afe66>

10. Pederson, A. (2024). Creating a workforce to align with AI investments in 2024. <https://trainingindustry.com/articles/workforcedevelopment/creating-a-workforce-to-align-with-aiinvestments-in-2024/>
11. Ransbotham, S. (2020). Reskilling talent to shrink technology gaps. *MIT Sloan Management Review*. <https://sloanreview.mit.edu/article/reskilling-talent-to-shrink-technology-gaps>
12. Santos, N. (2025, April 15). Why AI isn't optional anymore—It's a strategic imperative for modern businesses. [https://revglobalinc.com/uncategorized/why-ai-isnt-optional-anymore-its-a-strategic-imperative-for-modern-businesses/?utm\\_source=chatgpt.com](https://revglobalinc.com/uncategorized/why-ai-isnt-optional-anymore-its-a-strategic-imperative-for-modern-businesses/?utm_source=chatgpt.com)
13. Sayegh, E. (2024, June 4). The unstoppable march of artificial intelligence: From speculation to strategic imperative. <https://www.forbes.com/sites/emilsayegh/2024/06/04/theunstoppable-march-of-artificial-intelligence-fromspeculation-to-strategic>
14. Shi, Y., Gebauer, J., Kline, D. M., & Gillenson, M. L. (2024). Teaching a report-oriented business intelligence course: A pedagogical experience. *Journal of Information Systems Education*, 35(1), 73–85. <https://doi.org/10.62273/RTPL4395>
15. Skillsoft. (2024). *The C-suite perspective: 2024–2015 | Executive insights from the IT skills and salary report*. <https://www.skillsoft.com/the-c-suite-perspective>
16. Whiting, K. (2020, October 21). These are the top 10 job skills of tomorrow—And how long it takes to learn them. <https://www.weforum.org/stories/2020/10/top-10-workskills-of-tomorrow-how-long-it-takes-to-learn-them>
17. Zhang, Y. G., Dang, M. Y., & Albritton, M. D. (2024). Delivering a business analytics course focused on data mining for both technical and non-technical students. *Journal of Information Systems Education*, 35(1), 86–98. <https://doi.org/10.62273/MWCG1518>