



## Machine Learning-Based Frameworks for Employability Assessment and Skill Gap Analysis in Cloud and Cybersecurity

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**Abstract.** The global digital infrastructure is currently facing a "perfect storm" of rising cyber threats and a critical workforce shortage estimated at 4.7 million professionals. Despite the increasing output of graduates, industry research indicates that only 25–30% of engineering graduates are considered "job-ready". This systematic review evaluates current trends in using Machine Learning (ML) to automate student assessment and bridge the employability gap. By surveying academic databases and industry reports from 2017–2025, this paper identifies key findings regarding the efficacy of various classifiers—specifically Decision Trees (DT), Random Forests (RF), and XGBoost—in predicting graduate success and diagnosing technical discrepancies. The review highlights that while technical skills like programming are well-taught, significant gaps exist in Governance, Risk, and Compliance (GRC),

Cloud Security, and Analytical Thinking. This study concludes that there is an urgent need for a new, specialized ML-based framework to align educational outcomes with real-time cybersecurity demands.

**Keywords:** Machine Learning, Cloud Computing, Cybersecurity, Employability Assessment, Skill Gap Analysis, Systematic Review.

### Introduction

Cybersecurity has evolved from being a predominantly technical challenge within information and communication technologies (ICT) to becoming a critical pillar of national, economic, and organizational security. With the rapid digitalization of services, cloud adoption, and increasing reliance on interconnected systems, cyber threats now pose systemic risks that can disrupt critical infrastructure, financial stability, and public trust.



Research by [1]Babatope Olosunde reports that the average cost of a data breach in the United States has escalated to a record value of USD 9.48 million, underscoring the severe financial and operational consequences of cyber incidents. This sharp rise in breach-related losses highlights the urgent need for more proactive, intelligence-driven, and skill-oriented cybersecurity defense mechanisms.

Industry perspectives further reinforce this concern. Fortinet characterizes the current cybersecurity landscape as a “new normal,” where breaches are no longer viewed as exceptional events but as an anticipated reality for most organizations. In this context, the absence of adequately skilled cybersecurity professionals has emerged as a critical vulnerability. Knowledge gaps among graduates and entry-level professionals significantly weaken organizational defenses, often rendering advanced security technologies underutilized or ineffective. As cyber threats grow in complexity, the emphasis has shifted from merely deploying tools to ensuring that personnel possess the competencies required to configure, manage, and respond to sophisticated attacks effectively.

Despite increasing awareness, the cybersecurity skills gap continues to widen at an alarming rate, with recent estimates indicating a growth of 12.6% within a single year. Traditional educational models, which often rely on static curricula and theoretical evaluation methods, are increasingly unable to keep pace with the rapidly evolving demands of cloud computing, artificial intelligence, and modern cybersecurity practices. Empirical observations by Shakeeb Jumaan et al.

reveal that approximately 52% of organizations report that only a quarter or fewer of job applicants meet even the fundamental prerequisites required for cybersecurity roles. This mismatch between academic preparation and industry expectations highlights the limitations of conventional assessment approaches that emphasize grades over demonstrable, role-specific skills.

In response to these challenges, this review examines the potential of machine learning-based approaches to serve as a diagnostic bridge between academic training and industry requirements. By enabling automated, data-driven, and scalable assessment of student competencies, ML techniques offer a promising alternative to labor-intensive and subjective manual evaluation methods. Such approaches can facilitate continuous skill profiling, identify hidden gaps across cloud and cybersecurity domains, and support personalized learning pathways. Consequently, the integration of machine learning into employability assessment frameworks represents a critical step toward addressing the persistent skills gap and enhancing workforce readiness in the cybersecurity domain.

## Review Methodology

This study adopted a systematic, multi-stage literature search strategy to ensure comprehensive coverage of research related to cybersecurity skill gaps, employability assessment, and machine learning-based evaluation methods. Major scholarly databases, including IEEE Xplore, Scopus, and Google Scholar, were explored to capture both high-quality peer-reviewed publications and influential open-access studies. These databases were selected due



to their extensive indexing of engineering, computer science, and interdisciplinary research relevant to cybersecurity education and workforce development.

To retrieve targeted and relevant literature, structured search strings were formulated by combining key thematic concepts. The primary search query used was:

("cybersecurity skills gap" OR "workforce shortage") AND ("machine learning" OR "deep learning") AND ("employability" OR "curriculum").

This query design enabled the identification of studies addressing both the demand-side challenges of cybersecurity workforce readiness and the supply-side evaluation of educational and skill-assessment mechanisms.

The inclusion criteria were defined to ensure the relevance and timeliness of the reviewed literature. Only sources published between 2017 and 2025 were considered, reflecting the rapid evolution of cybersecurity technologies and pedagogical approaches. This timeframe was specifically chosen to incorporate recent developments such as Generative Artificial Intelligence, cloud-native security, and Zero Trust architectures, which have significantly reshaped skill requirements and industry expectations. Publications were required to explicitly address cybersecurity education, employability assessment, skill gap analysis, or the application of machine learning techniques in these contexts.

## Background and Fundamentals

Information Literacy: The Foundational Competency

Information Literacy (IL) is established as a cornerstone competency for cybersecurity professionals. According to [3]Johannes Steinrücke et al., IL is the ability to recognize when information is needed and to locate, evaluate, and use that information effectively to solve complex problems. In high-stakes environments like crisis management, decision-makers must successfully merge an intuitive approach (built through experience) with an analytical approach (based on contextual data).

The American Library Association (ALA) further delineates this competency into four primary standards relevant to automated assessment:

1. Determining the nature and extent of information required.
2. Accessing information efficiently and effectively.
3. Evaluating sources critically and incorporating them into a personal knowledge base.
4. Using information to accomplish a specific strategic purpose.

## The Cloud and Mechatronics Integration

In the modern digital landscape, particularly within the cloud domain, cybersecurity involves a deep integration of mechanical, electrical, and computer systems. This interdisciplinary field, often referred to as mechatronics, is essential for the design and development of automated systems and robotics. As Szufang Chuang et al. note, the advancement of these technologies requires middle-skilled employees to acquire new expertise in programming, maintaining, and repairing AI-powered robotic systems, as human-



machine integration becomes increasingly intertwined.

## The U-Shaped Workforce Structure

The contemporary labor market is undergoing a significant transformation described as a "U-shaped" structure. [3]Szufang Chuang et al. explain that technological advances, specifically in Artificial Intelligence (AI) and Machine Learning (ML), have polarized job demands:

1. High-Skilled Cognitive Non-routine Jobs: These involve abstract tasks, typically requiring a college degree (e.g., Data Scientists, AI Researchers).
2. Low-Skilled Manual Non-routine Jobs: These involve physical tasks and personal traits (e.g., personal services).
3. Middle-Skilled Routine Positions: These manual or cognitive roles involve precise, repetitive procedures and are the most susceptible to being displaced by automation.

## Reskilling and Upskilling Pathways

To ensure career sustainability in this evolving landscape, continuous development through reskilling (learning entirely new skills) and upskilling (enhancing existing skills) is mandatory[1]. Research by [4]Chuang et al. provides a strategic roadmap for this transition. For example, middle-skilled workers such as CNC tool operators can be upskilled into CNC tool programmers, which not only offers a "bright outlook" with faster-than-average growth but also significantly increases earning potential. This initial step serves as seed talent for even higher-skilled roles, eventually leading to specialized

positions in Data Science and AI engineering.

## Analogy for the Skills Deficit

The current state of the cybersecurity workforce can be understood through the potable water analogy[4]. While candidates (water) exist abundantly in nature, there is an acute and dangerous shortage of skilled professionals (potable water) who are ready for immediate industry consumption. Your proposed framework acts as the purification system, identifying exactly which raw talents need to be "tr[4]eated" with specific reskilling modules to meet industry standards literature was categorized into two primary groups: manual-based approaches and automated-based approaches. Manual-based approaches included studies relying on expert-driven frameworks, competency taxonomies, and standardized knowledge bodies such as the Cyber Security Body of Knowledge (CyBOK)[5]. In contrast, automated-based approaches encompassed research employing machine learning-driven predictive modeling, data analytics, and intelligent assessment systems for evaluating skills, forecasting employability, or identifying competency gaps. This classification facilitated a comparative analysis of traditional and data-driven methods, highlighting existing limitations and motivating the need for an integrated, ML-based employability assessment framework.

## Classification of Existing Work

Current research categorizes efforts to bridge the skill gap into Technical Knowledge Areas (KAs) and Professional Attributes.



**Table 1. The disconnect-graduate perception vs. Industry reality**

Attribute	Graduates Perception	Industry Expectation	Demand Status
Coding Skills	High	Very High	Essential technical requirement
Cloud Security	Moderate	Critical	Hardest role to fill
Soft Skills	Moderate	High	Critical for final decisions
Experience	Low	Moderate to High	Top hiring priority
Analytical Thinking	High	High	Under-represented in graduates

Research by Christopher A. Ramezan identifies nine sub-fields—including[6] architecture, auditing, and GRC—each requiring distinct certifications and programming expertise. Notably, 89% of IT leaders prefer candidates with industry certifications like CISSP over four-year degrees alone.

### Comparative Analysis

ML models can predict employability status with nearly 100% accuracy using student features.

Algorithm	Accuracy (%)	Precision	Recall
Decision Tree (DT)	100%	1.00	1.00
Logistic Regression	98%	0.96	0.99

XGBoost	95.3%	1.00 (Class 1)	1.00 (Class 0)
Random Forest (RF)	93.0%	0.94	0.97
KNN	93.8%	0.96	0.95

Research by Iqbal H. Sarker argues that effectiveness depends on "correlated-feature selection" to reduce model complexity. Švábenský et al. demonstrated that clustering (e.g., OPTICS) can identify compact groups of students with similar behavioral patterns, allowing for targeted feedback.

### Applications and Use Cases

**Automated Assessment:** Valdemar Švábenský et al. analyzed 8,834 commands to reveal typical behavior and mistakes in terminal usage. **Cloud-Based Stress Management:** Tian Lan and Zhanfang Sun investigated how cloud collaboration tools influence job search stress and psychological well-being. **Unobtrusive Skills Assessment:** Johannes Steinrücke et al. developed methods using in-game indicators in serious games to assess Information Literacy without breaking the flow of gameplay.

### Open Challenges and Research Gaps

**Curriculum Lag:** Borja Jerman Blažič notes that higher education institutions are often slow to adapt to technology changes, leading to discrepant knowledge. **Linguistic Variance:** Francois Goupil et al. suggest that job ads use varied terminology, making exact keyword matching insufficient and requiring fuzzy logic. **Data Scarcity:** Smaller sample sizes in specific sub-fields like auditing and education limit model generalizability.

## Future Research Directions

**Live Data Mining:** Valdemar Švábenský et al. propose incorporating live mining during ongoing training to provide real-time hints to stuck trainees. **AI Explainability:** Implementing SHAP and LIME to provide more insight into how specific features affect placement predictions. **Sector-Specific Initiatives:** Babatope Olosunde recommends developing initiatives targeted at healthcare and energy sectors where the impact of the skills gap is most severe.



**Fig. 1.** Proposed Integrated Framework Workflow

For citations of references, we prefer the use of square brackets and consecutive numbers. Citations using labels or the author/year convention are also acceptable. The following bibliography provides a sample reference list with entries for journal articles [1], an LNCS chapter [2], a book [3], proceedings without editors [4], as well as a URL [5].

## Conclusion

The persistent global workforce deficit of 4.7 million professionals cannot be resolved through traditional academic expansion alone. Current review findings reveal that while existing ML models achieve high accuracy in predicting binary employability, they often function as "black boxes" lacking diagnostic granularity. Academic curricula remain well-balanced in programming but are significantly under-represented in Cloud Security and GRC. Therefore, there is a definitive and urgent

need for a new Machine Learning-based framework specifically designed for the employability assessment and skill gap analysis of Cloud and Cybersecurity students to foster global economic resilience.

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