A Computational Framework for Skill Gap Analysis and Employability Measurement

Integrating Labour Market Data, Skills Taxonomies and Artificial Intelligence

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Date: March 2026

Preprint Version

Abstract

Rapid technological change, automation and artificial intelligence are transforming labour markets and redefining professional competencies. Traditional career representation tools, particularly the curriculum vitae (CV), rely on static descriptions of education and experience and therefore struggle to capture the dynamic relationship between individual skills and evolving labour market demand.

This paper proposes a computational framework for measuring employability through dynamic skill analysis. The framework integrates labour market data, structured skill taxonomies and artificial intelligence techniques to quantify the alignment between an individual's competencies and occupational requirements.

At the core of the model lies the **Skill Gap Algorithm**, which represents individuals and occupations as vectors in a multidimensional skill space and calculates their similarity using vector distance metrics. The model also incorporates labour market trend weighting to account for the evolving demand for specific competencies.

The framework contributes to the emerging field of **data-driven career guidance**, proposing that employability should be understood not as a static attribute of individuals but as a dynamic alignment between competencies and labour market structures.

The proposed approach provides a foundation for intelligent career guidance systems capable of generating personalised reskilling pathways and supporting evidence-based career decision-making in rapidly changing labour markets.

Keywords: Employability, Skill gap analysis, Artificial intelligence, Labour market analytics, Career guidance, Skills taxonomy, Reskilling, Future of work, Human capital analytics

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1. Introduction

Labour markets are undergoing a structural transformation driven by technological innovation, globalisation and the rapid diffusion of digital technologies. The emergence of artificial intelligence, automation and platform economies has accelerated the pace at which professional competencies become obsolete while simultaneously creating demand for new skill combinations.

Recent reports highlight the scale of this transformation. The **World Economic Forum Future of Jobs Report (2023)** estimates that nearly half of the global workforce will require significant reskilling or upskilling within the next decade. Similarly, the **OECD Skills Outlook (2023)** identifies growing mismatches between workforce competencies and labour market needs across many advanced economies.

Traditional career planning tools are poorly equipped to analyse these dynamics. The curriculum vitae (CV), for example, primarily functions as a retrospective document summarising past experiences rather than as an analytical instrument capable of evaluating alignment between competencies and labour market demand.

This limitation has stimulated growing interest in **data-driven career guidance**, where computational models analyse labour market data to identify skill demand patterns and support career decision-making.

This paper introduces a computational framework for measuring employability through **skill distance analysis**, proposing a model referred to as the **Skill Gap Algorithm**.

2. The Changing Nature of Employability

The concept of employability has evolved significantly over recent decades.

Early theoretical perspectives defined employability primarily as the ability to obtain employment, often associated with educational qualifications or job search skills.

More recent interpretations emphasise employability as a **multidimensional construct**, incorporating:

- adaptability
- transferable competencies
- career self-management

From an economic perspective, employability increasingly reflects the degree to which individuals possess competencies valued in the labour market.

This interpretation aligns with theories of **skill-biased technological change**, where technological innovation increases demand for certain types of skills while reducing demand for others.

Empirical research using large labour market datasets shows that the economic value of specific skills may decline rapidly as technologies evolve, reinforcing the need for continuous skill adaptation.

These dynamics suggest that employability should not be considered a static attribute but rather a **dynamic relationship between individuals and labour market structures**.

3. Skills Taxonomies and Labour Market Data

The availability of structured labour market data has enabled new analytical approaches to studying skill demand.

One of the most comprehensive frameworks is the **European Skills, Competences, Qualifications and Occupations (ESCO)** taxonomy developed by the European Commission. ESCO provides a multilingual ontology linking occupations, skills and qualifications.

ESCO contains thousands of occupations and more than ten thousand structured skills organised within a hierarchical classification.

Similarly, initiatives such as the **Global Skills Taxonomy** developed by the World Economic Forum aim to standardise skill representations across industries and geographical regions.

These taxonomies allow computational systems to transform **unstructured professional data** into structured representations suitable for analytical processing.

4. Limitations of Traditional Career Representation

Despite the increasing importance of skills in labour market analysis, traditional career documentation systems remain largely static.

The curriculum vitae presents several limitations when used as an analytical tool:

First, CVs are descriptive rather than analytical. They list qualifications and experiences but do not evaluate their relevance relative to labour market demand.

Second, skill descriptions in CVs are typically unstructured and inconsistent, making systematic comparison across individuals difficult.

Third, CVs fail to capture the **temporal dynamics of skill demand**, where competencies lose or gain value as technologies evolve.

These limitations highlight the need for analytical frameworks capable of transforming unstructured career data into structured skill profiles.

5. Skill Extraction and Normalisation

The first stage of the proposed framework involves extracting skills from unstructured documents such as CVs, professional profiles or job descriptions.

Recent advances in **Natural Language Processing (NLP)** enable automated identification of skills and competencies within textual data.

Techniques such as **Named Entity Recognition (NER)** can identify mentions of technologies, professional competencies or work activities. Machine learning models can then classify these entities according to predefined skill taxonomies.

After extraction, skills must be **normalised** to ensure comparability.

For example, expressions such as:

- Python programming
- coding in Python
- Python development

may refer to the same underlying skill.

Mapping extracted skills to a standard taxonomy such as ESCO enables the representation of professional profiles as **structured skill vectors**.

6. The Skill Gap Algorithm

The core idea of the Skill Gap Algorithm is to represent both individuals and occupations as vectors within a multidimensional skill space.

Let:

A = vector representing an individual's skills
B = vector representing the skill requirements of a target occupation

The degree of alignment between these vectors can be measured using **cosine similarity**, a widely used metric in information retrieval and machine learning.

The employability score can be expressed as:
Employability Score = $(A \cdot B) / (||A|| \ ||B||)$

Where:

$A \cdot B$ represents the dot product between vectors
$||A||$ and $||B||$ represent vector magnitudes

The resulting value ranges between **0 and 1**, indicating the degree of similarity between the individual's competencies and occupational requirements.

Higher scores indicate stronger alignment between skills and occupational demand.

7. Incorporating Labour Market Trends

Similarity metrics alone cannot capture temporal changes in labour market demand. To address this limitation, the model incorporates a **trend weighting factor (T)** based on labour market data.

This factor may be derived from:

- frequency of skill mentions in job postings
- growth rates of skill demand
- industry adoption patterns

The employability score can therefore be extended as:

Employability Score = cosine similarity (A,B) × T

Where **T** captures the relative growth or decline of specific skills within the labour market.

This extension enables the model to reflect evolving economic and technological conditions.

8. Applications in Career Guidance Systems

The framework has several potential applications.

First, the algorithm can generate **personalised skill gap analyses**, identifying competencies individuals need to acquire to reach specific career goals.

Second, it can support **adaptive learning pathways**, recommending educational programmes aligned with identified skill gaps.

Third, aggregated analysis of skill gaps across populations may reveal **labour market trends**, informing policy decisions related to education and workforce development.

These systems represent a shift from traditional career guidance models toward **data-driven career navigation tools**.

9. System Architecture for Data-Driven Career Guidance

The proposed framework can be implemented within intelligent career guidance systems composed of three main layers:

1. Skill Extraction Layer
Processes unstructured documents using NLP techniques to identify and normalise skills.

2. Skill Gap Analysis Layer
Represents profiles and occupations as skill vectors and calculates similarity scores.

3. Recommendation Layer
Generates personalised learning recommendations based on identified skill gaps and labour market trends.
Such architectures enable continuous adaptation as labour market conditions evolve.

10. Discussion

Computational approaches to employability measurement open new possibilities for analysing labour market dynamics.

By representing professional competencies as structured data and analysing their relationship with occupational demand, it becomes possible to quantify employability in ways previously not feasible.

However, several challenges remain.

Skill extraction algorithms may produce errors, and labour market datasets may contain biases depending on their source.

Future research should explore hybrid models combining quantitative skill analysis with qualitative factors such as career motivation, organisational context and social capital.

11. Conclusion

This paper proposes a computational framework for analysing employability through skill distance measurement.

The **Skill Gap Algorithm** conceptualises employability as a dynamic relationship between competencies and labour market structures rather than as a fixed individual attribute.

By integrating skill extraction, taxonomy normalisation and vector similarity metrics, the model provides a foundation for intelligent career guidance systems capable of generating personalised reskilling recommendations.

As labour markets continue to evolve, analytical tools capable of interpreting complex skill ecosystems will become increasingly important for individuals, institutions and policymakers navigating the future of work.

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