

Using Natural Language Processing to Explore Alignment Between Skill Taxonomies

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Abstract

We examine alignment at both node and taxonomy levels across four major skill taxonomies. Using semantic similarity and cluster analysis, results indicate uneven overlap: some skills converge, and some taxonomies interleave more than others. These findings could inform educational assessment by clarifying construct validity claims and score interpretations across frameworks.

1 Introduction

Skill taxonomies are increasingly used to define learning outcomes, credentials, and job requirements (Campion et al., 2011; Sánchez and Levine, 2009) yet major frameworks differ in scope, granularity, and construct framing, making it unclear when they describe the same underlying competency (Teyssier-Roberge et al., 2025; Weber et al., 2025).

From a construct-validity perspective, these differences matter because alignment across taxonomies is defensible only when competencies defined by different frameworks appear to converge on the same underlying constructs, thus supporting comparable interpretations (Cronbach and Meehl, 1955; Messick, 1995). This issue has direct implications for assessment design, the underlying validity arguments connecting evidence from assessments to interpretable scoring approaches, and the comparability of inferences that can be drawn from skills assessments across various educational and workforce contexts.

Methods involving artificial intelligence (AI) and natural language processing (NLP) may support competency mapping, taxonomy crosswalks, curriculum alignment, digital credentials, and workforce signaling, often by inferring similarity from text representations of skill statements (Putka et al., 2023; Reimers and Gurevych, 2019).

2 Research Aims

Against this backdrop, the present study uses NLP to explore cross-taxonomy alignment at two different levels. First, we examine the similarity of skill labels and descriptors across selected taxonomies. Second, we examine the extent to which pairs of skill taxonomies overlap with one another. These objectives lead to two main research questions:

(RQ1) To what extent are pairs of skill labels and descriptions between pairs of skill taxonomies semantically similar?

(RQ2) To what extent are pairs of skill taxonomies interleaved with one another?

3 Methods

We analyzed distinct skill nodes from four widely used taxonomies: U.S. Bureau of Labor Statistics Employment Projections (BLS EP; 17 nodes), O*NET (215), World Economic Forum Global Skills (WEF; 117), and ESCO (414, after removal of 122 child skill nodes identical to parent nodes and 111 nodes with no descriptors).

These frameworks were selected because they are widely referenced but differ in purpose, structure, and construct framing. BLS EP offers a small set of broad categories for occupational projections and workforce analysis (Dey et al., 2024). O*NET is a large U.S. occupational system spanning multiple descriptor domains and levels of abstraction (Levine and Oswald, 2013; Peterson et al., 2001). WEF is a taxonomy that combines skills, knowledge, abilities, and attitudes to support global workforce strategy (World Economic Forum, 2021a, 2025). ESCO is a multilingual European classification system designed to support interoperability across employment, education, and training contexts, with skill statements that are more action- and task-oriented (European Commission, 2017; Ospino Hernandez, 2018).

All taxonomies reflect publicly available skill

taxonomies and were retrieved from their respective source in November 2025. The BLS Employment Projections (EP) skills data were scraped from the U.S. Bureau of Labor Statistics website (U.S. Bureau of Labor Statistics, 2025). O*NET descriptors—including abilities, interests (general and basic), work styles, and work values—were obtained from the O*NET Online descriptor pages, with data either scraped or downloaded where structured files (e.g., CSV) were available (O*NET Resource Center, 2025b,c,d). O*NET knowledge, skills, and work activities were downloaded from the O*NET Center content model framework files (O*NET Resource Center, 2025a). These elements were intentionally selected from the O*NET content model because they reflect generalized worker characteristics and requirements that are not occupation-specific, but instead capture broad capacities, preferences, and activities that individuals may need to demonstrate across a wide range of occupational contexts. The World Economic Forum (WEF) skills taxonomy was downloaded directly from the published report (World Economic Forum, 2021b). The ESCO taxonomy (version 1.2.0) was downloaded from the official ESCO portal (European Commission, 2025).

After retrieving each skill taxonomy, their formats were standardized into a common format to enable cross-taxonomy comparisons and integration. This allowed for a common analytic structure that preserved taxonomy identity, taxonomy type, and hierarchical level while enabling direct comparison across taxonomies. Each skill node was represented as a single text string combining its skill label and description, and Sentence-BERT (SBERT) embeddings (model all-MiniLM-L6-v2) were used to place all nodes in a shared semantic space optimized for textual similarity (Reimers and Gurevych, 2019). Pairwise cosine similarity was then computed across all node pairs to estimate semantic convergence. To address RQ1, we examined skill node pairs between all six cross-taxonomy pairings: BLS EP ↔ O*NET, BLS EP ↔ WEF, BLS EP ↔ ESCO, O*NET ↔ WEF, O*NET ↔ ESCO, and WEF ↔ ESCO.

To address RQ2, we conducted separate Hierarchical Agglomerative Clustering (HAC) analyses using the Ward.D2 linkage method with the *stats* package in the R statistical environment using the matrix of cosine similarity estimates for each taxonomy pair. The optimal number of clusters (k) was selected via an agglomeration-gap statis-

tic, which identifies the largest gap in dendrogram merge heights (bounded between $k=2$ and $k=12$). We computed cophenetic correlations (r_{coph}) to evaluate how faithfully each dendrogram preserved the original pairwise distances, and we conducted silhouette analyses and estimated silhouette widths ($\bar{s}$) for each node to quantify how similar a node is to others within its assigned cluster relative to its similarity to the nearest alternative cluster. We also considered both within-cluster ($\bar{w}$) and between-cluster ($\bar{b}$) similarities, as well as their difference, to evaluate the separation between clusters.

In pursuit of these questions, this study serves as an example of AI in measurement science by using semantic similarity as a source of evidence about construct comparability and pairwise clustering as a second-stage analysis to show how alignment between skill taxonomies may be evidenced.

4 Results

4.1 Semantic similarity of skill labels and descriptions between taxonomy pairs (RQ1)

Addressing RQ1, semantic similarity estimates indicated meaningful but uneven convergence across the six taxonomy pairs (see Figure 1). For interpretive purposes, cosine similarity values may be interpreted as follows: very high ($>.80$), mid-high ($\approx .60-.80$), moderate ($\approx .40-.60$), mid-low ($\approx .25-.40$), and low ($<.25$).

In general, high-similarity pairs were concentrated in analytic and cognitive domains (e.g., mathematics, problem solving, and analytical reasoning), interpersonal and service domains (e.g., social perceptiveness, service orientation), and management and leadership domains. For example, within BLS EP ↔ ESCO, the BLS category Mathematics showed relatively strong alignment with ESCO concepts such as mathematics (cosine=.768) and processing information, ideas and concepts (cosine=.658), indicating convergence around core analytic competencies despite differences in hierarchy and scope. These cases illustrate how highly similar pairs often reflect shared underlying constructs expressed through partially overlapping definitions rather than identical labels.

We found that BLS EP ↔ O*NET produced the highest mean cross-taxonomy similarity, consistent with their shared foundation in U.S. occupational analysis. This result is substantively meaningful because these frameworks are not independent ab-

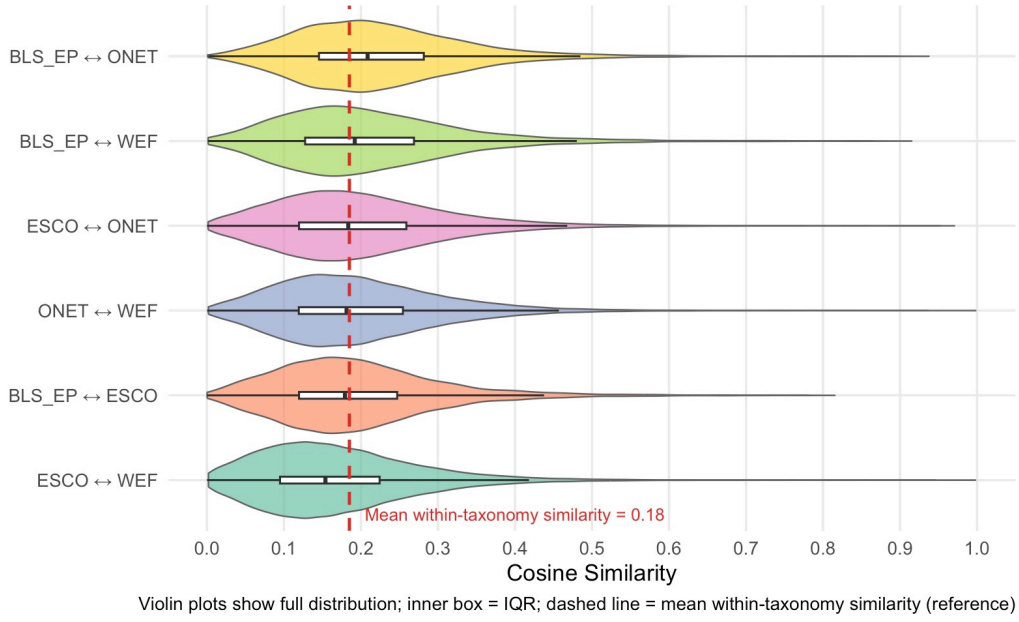


Figure 1: Cross-taxonomy cosine similarity distributions by taxonomy pair.

stractions of the skill space but rather share a lineage (Dey et al., 2024).

O*NET ↔ ESCO showed the second-highest overall alignment based on average cosine similarity, particularly for technical, task-oriented, and operational skills. Both frameworks emphasize process and task descriptions, which appears to facilitate semantic alignment even across their different geographic and institutional origins.

BLS EP ↔ WEF showed moderate alignment based on average cosine similarity. Broad skill families (e.g., analytic thinking, interpersonal skills, leadership, and creativity) showed reasonable correspondence, but alignment was attenuated in domains where WEF extends into attitudinal constructs (e.g., self-efficacy, values and ethics, empathy) that have no direct counterpart in BLS EP’s broad-category structure.

O*NET ↔ WEF also showed moderate alignment based on cosine similarity, with WEF’s blending of cognitive and technology constructs producing strong alignment in core cognitive and interpersonal domains alongside weaker alignment in WEF’s more distinctive dispositional and meta-skill content. More specifically, the weaker alignment between WEF and the other frameworks reflects a broadening of what counts as a workforce-relevant competency in newer frameworks, which increasingly incorporate dispositional, interpersonal, and self-regulatory constructs alongside more traditional job-analysis descriptors (Liu et al.,

2025).

For each of the six cross-taxonomy pairs, the node pair with the highest cosine similarity is shown in Table 1, with full labels, descriptions, and parent nodes, illustrating the strongest points of conceptual convergence across frameworks. The lowest-similarity pairs are shown in Table 2.

Many high-similarity pairs involved broad constructs that are widely recognized across frameworks (e.g., critical thinking, problem solving, communication, and mathematical reasoning) suggesting that these represent a shared set of competencies that different taxonomies have independently converged upon including. Alternatively, they may reflect related development lineages in which frameworks adopt and refine common work-analysis constructs and wording.

For the lowest-similarity cases, these examples may illustrate key distinctions in each taxonomy’s emphasis. We include these only to show how this approach could distinguish related from unrelated skill nodes and not to suggest that pairs with low similarity estimates be treated as opposing skills.

4.2 Cluster analysis to examine general overlap between taxonomy pairs (RQ2)

Across all six taxonomy pairs, cophenetic correlations were uniformly low, ranging from $r_{\text{coph}} = -0.122$ (BLS EP ↔ ESCO) to $r_{\text{coph}} = 0.156$ (O*NET ↔ WEF). All values fall well below the 0.70 threshold, indicating that the Ward.D2 den-

Table 1: Highest similarities of cross-taxonomy skill pair per taxonomy pair

Taxonomy A	Skill Label A	Description A	Taxonomy B	Skill Label B	Description B	Cosine Sim.
WEF	Assisting and supporting co-workers	Assisting and supporting colleagues, managers, volunteers and other co-workers in the performance of their tasks or in the operations of a business unit.	ESCO	assisting and supporting co-workers	Assisting and supporting colleagues, managers, volunteers and other co-workers in the performance of their tasks or in the operations of a business unit.	1.000
WEF	Writing	Communicating effectively in writing as appropriate for the needs of the audience.	O*NET	Writing	Communicating effectively in writing as appropriate for the needs of the audience.	1.000
ESCO	building and developing teams	Encouraging team members and building a relationship of mutual trust, respect and cooperation. Stimulating teambuilding activities.	O*NET	Developing and Building Teams	Encouraging and building mutual trust, respect, and cooperation among team members.	0.941
BLS EP	Problem solving and decision making	Identifies complex problems, determines accuracy and relevance of information, uses judgment to develop and evaluate options, and implements solutions	O*NET	Making Decisions and Solving Problems	Analyzing information and evaluating results to choose the best solution and solve problems.	0.884
BLS EP	Critical and analytical thinking	Applies logic and reasoning to analyze information, identify strengths and weaknesses of various approaches and solutions to problems, and draw conclusions	WEF	Analytical thinking	Capacity to break down concepts and complex ideas into basic or fundamental principles. Includes critical thinking, whereby judgements are made by analysing and interpreting facts and information.	0.853
BLS EP	Creativity and innovation	Uses imagination to develop new insights in situations and applies innovative solutions to problems; designs, creates, and implements cutting-edge processes, ideas, or products, including artistic contributions	ESCO	thinking creatively and innovatively	Generate new ideas or combine existing ones to develop innovative, novel solutions.	0.77

Table 2: Lowest similarity of cross-taxonomy skill pair per taxonomy pair

Taxonomy A	Skill Label A	Description A	Taxonomy B	Skill Label B	Description B	Cosine Sim.
WEF	Adaptation to change	Altering one's attitude or behaviour to accommodate modifications in the workplace.	ESCO	classical languages	All dead languages, no longer actively used, originating from various periods in history [...]	-0.156
ESCO	classical languages	All dead languages, no longer actively used, originating from various periods in history [...]	O*NET	Coordination	Adjusting actions in relation to others' actions.	-0.144
WEF	Risk management	Assessing, prioritising and mitigating the effect of uncertainty on objectives, to enhance institutional resilience.	O*NET	Artistic	Work involves creating original visual artwork, performances, written works, food, or music for a variety of media, or applying artistic principles to the design of various objects and materials. [...]	-0.113
BLS EP	Problem solving and decision making	Identifies complex problems, determines accuracy and relevance of information, uses judgment to develop and evaluate options, and implements solutions	ESCO	classical languages	All dead languages, no longer actively used, originating from various periods in history...	-0.093
BLS EP	Customer service	Works with external customers (for example, clients, patients, and consumers) [...]	WEF	Risk management	Assessing, prioritising and mitigating the effect of uncertainty on objectives, to enhance institutional resilience.	-0.089
BLS EP	Customer service	Works with external customers (for example, clients, patients, and consumers) [...]	O*NET	History and Archeology	Knowledge of historical events and their causes, indicators, and effects on civilizations and cultures.	-0.047

drograms do not faithfully preserve pairwise distances and that the tree topology should not be over-interpreted. Similarly, mean silhouette widths were uniformly weak, spanning from $\bar{s} = -0.005$ (BLS EP $\leftrightarrow$ ESCO and BLS EP $\leftrightarrow$ O*NET) to $\bar{s} = 0.034$ (BLS EP $\leftrightarrow$ WEF), with all values falling below the 0.25 threshold for “reasonable” cluster structure.

Despite the uniformly low global diagnostics, inspection of individual clusters revealed seemingly coherent skill groupings within every taxonomy pair. In particular, the BLS EP $\leftrightarrow$ ESCO solution ($n = 370$, $k = 8$, $r_{\text{coph}} = -0.122$, $\bar{s} = -0.005$) produced 5 of 8 mixed clusters (see Table 3). One well-defined group united BLS EP’s *Creativity and innovation* with ESCO’s *thinking creatively and innovatively, creating artistic, visual or instructive materials, and creating artistic designs or performances* (cluster-level $\bar{s} = 0.085$, the highest among mixed clusters in this pair). A communication-oriented cluster paired BLS EP’s *Speaking and listening* and *Writing and reading* with ESCO’s *communicating, obtaining information verbally, and presenting information*.

The BLS EP $\leftrightarrow$ O*NET solution ($n = 232$, $k = 8$, $r_{\text{coph}} = -0.101$, $\bar{s} = -0.005$) exhibited a high proportion of clusters with nodes from both taxonomies (7/8), indicating that most clusters were taxonomically mixed. Substantively, the clusters seemed interpretable. BLS EP’s *Problem solving and decision making* and *Critical and analytical thinking* merged with O*NET’s *Making Decisions and Solving Problems*, *Complex Problem Solving*, and *Critical Thinking* (C4, cluster $\bar{s} = 0.127$). BLS EP’s *Creativity and innovation* mapped onto O*NET’s *Thinking Creatively*, *Applied Arts and Design*, and *Fine Arts* (C7, cluster $\bar{s} = 0.116$). A mechanical/physical cluster linked BLS EP’s *Mechanical* and *Fine motor* to O*NET’s *Repairing and Maintaining Mechanical Equipment*, *Handling and Moving Objects*, and *Controlling Machines and Processes* (C3, cluster $\bar{s} = 0.090$).

The BLS EP $\leftrightarrow$ WEF pair ($n = 134$, $k = 11$, $r_{\text{coph}} = 0.094$, $\bar{s} = 0.034$) achieved the highest mean silhouette width among all pooled solutions, consistent with the relatively smaller node set and the greater conceptual alignment between BLS EP’s competencies and WEF’s future-of-work skills. Ten of the 11 clusters included nodes from both taxonomies. The strongest individual cluster ($\bar{s} = 0.124$) linked BLS EP’s *Customer service* with WEF’s *Customer service*, *Customer relationship management*, and *Customer experience*.

A literacy-focused cluster ($\bar{s} = 0.094$) united BLS EP’s *Writing and reading* and *Speaking and listening* with WEF’s *Writing*, *Speaking*, *Multi-lingualism*, and *Reading*. BLS EP’s *Creativity and innovation* paired with WEF’s *Creative thinking* and *Creativity and problem solving* ($\bar{s} = 0.100$).

The ESCO $\leftrightarrow$ O*NET analysis pooled the largest node set ($n = 568$) and selected the maximum $k = 12$. Its cophenetic correlation of $r_{\text{coph}} = 0.144$ was the second-highest among all pairs, and its mean silhouette width of $\bar{s} = 0.021$ indicated weak but positive structure. All 12 clusters were taxonomically mixed. This pair also had the highest mean within-cluster similarity at the solution level ($\bar{w} = 0.156$), suggesting that ESCO and O*NET occupy the most overlapping region of the cross-taxonomy skill space.

The ESCO $\leftrightarrow$ WEF solution ($n = 470$, $k = 10$, $r_{\text{coph}} = 0.088$, $\bar{s} = 0.012$) produced all 10 mixed clusters, though the largest (C10, $n = 91$) was dominated by ESCO nodes (89%) with very low within-cluster similarity ($\bar{w} = 0.042$). This pair also recorded the lowest overall separation ($\bar{w} - \bar{b} = 0.049$), indicating that between-cluster similarity remained high relative to within-cluster cohesion. The most cohesive mixed cluster ($\bar{s} = 0.100$) was a relatively small group ($n = 16$). An environmentally themed cluster (C4, $n = 24$) uniquely brought together WEF’s *Sustainable and efficient resource usage*, *Environmental awareness*, and *Adopting green technologies* with ESCO’s *applying environmental skills and competences* and *advising on environmental issues*, an alignment seemingly absent from other taxonomy pairs and reflecting the distinctive green-skills emphasis shared by these two frameworks.

Finally, the O*NET $\leftrightarrow$ WEF pair ($n = 332$, $k = 8$, $r_{\text{coph}} = 0.156$, $\bar{s} = 0.025$) achieved the highest cophenetic correlation of any pooled solution. All 8 clusters were taxonomically mixed. A quantitative-reasoning cluster (C5, $n = 32$) grouped WEF’s *Calculating and estimating*, *Mathematical and statistical thinking*, *Data analysis and mathematical modelling*, and *Computational thinking* alongside O*NET nodes. A communication cluster (C6, $n = 34$) united WEF’s *Speaking*, *Writing*, and *Multi-lingualism* with O*NET descriptors. The most cohesive group was a marketing-and-service cluster (C8, $n = 15$, cluster $\bar{s} = 0.084$) that paired WEF’s *Customer service*, *Digital marketing*, and *Sales, communication and marketing of products and services* with O*NET’s *Sales and*

Table 3: Cross-taxonomy cluster summary

Taxonomy Pair	Nodes	Clusters (k)	Within ($\bar{w}$)	Between (b)	Sep. ($\bar{w}-b$)	Entropy	Mixed Clusters
BLS EP $\leftrightarrow$ ESCO	370	8	0.077	0.035	0.042	1.300	5
BLS EP $\leftrightarrow$ O*NET	232	8	0.127	0.047	0.080	1.924	7
BLS EP $\leftrightarrow$ WEF	134	11	0.128	0.050	0.078	1.609	10
ESCO $\leftrightarrow$ O*NET	568	12	0.156	0.085	0.071	1.525	12
ESCO $\leftrightarrow$ WEF	470	10	0.107	0.058	0.049	1.124	10
O*NET $\leftrightarrow$ WEF	332	8	0.137	0.079	0.058	1.699	8

Marketing, Marketing/Advertising, and Service Orientation.

5 Conclusions

The results point to a few potential overarching implications. First, several very high-similarity skill nodes reflected shared broad constructs (e.g., WEF “Writing” $\leftrightarrow$ O*NET “Writing,” cosine=1.000), while some low-similarity matches seemed to reflect taxonomy scope non-overlap or divergent construct framings. Accordingly, the findings support the use of semantic similarity estimates as a tool for systematically identifying likely correspondences between skill taxonomies.

Second, the uniformly low cophenetic correlations ($-0.122 \leq r_{\text{coph}} \leq 0.156$) and mean silhouette widths ($-0.005 \leq \bar{s} \leq 0.034$) from the cluster analysis suggest that cross-taxonomy skill spaces may not be well described by compact clusters. This finding suggests the importance of exercising caution against treating any single cluster solution as a definitive “crosswalk” between taxonomies and instead supports the use of continuous similarity scores or looser cluster memberships, when mapping categories of skills across taxonomies.

Third, despite the weak global structure, the content of the clusters seemed remarkably interpretable across pairs. The pairs involving BLS EP consistently produce large residual clusters of unmatched nodes from the more granular taxonomy (ESCO, O*NET, or WEF), reflecting BLS EP’s much coarser granularity given it consists of a flat level with 17 skill nodes. Among the non-BLS EP pairs, ESCO $\leftrightarrow$ O*NET exhibits the strongest overlap ($\bar{w} = 0.156$, 12/12 mixed clusters), while ESCO $\leftrightarrow$ WEF shows the weakest separation ($\text{Sep.} = 0.049$). This may reflect WEF’s inclusion of attitudinal categories that are beyond the occupational skill domains that ESCO was designed to describe. These patterns suggest that harmonization efforts may want to prioritize the ESCO $\leftrightarrow$ O*NET axis, where semantic conver-

gence is greatest, while treating emergent WEF competencies and broad BLS EP labels as complementary lenses rather than direct translation targets.

Semantic similarity and cluster analyses may be useful methods for identifying likely correspondences and recovering information about differences and overlap between skills taxonomies. Consistent with prior work, coherence between skill taxonomies may be most defensible when viewed as a continuum and at higher levels of abstraction, whereas more discrete skill mappings are less stable and more dependent on contextual interpretation (Teyssier-Roberge et al., 2025; Weber et al., 2025). The strength and coherence of that overlap should also be expected to vary substantially based on the underlying assumptions and purpose of the taxonomies being compared.

The methods such as those used in the present study are best understood as decision-support tools that organize evidence for human judgment, rather than replacements for theory or expert interpretation. We emphasize that semantic similarity alone does not establish construct equivalence, and is likely to be most informative when combined with theoretical considerations of target constructs, knowledge of the skill taxonomies, and expert review (Messick, 1995; Putka et al., 2023).

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