

TECHNICAL NOTE

Generative Al's Impact on the Workforce: A Technical Framework

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Summary

This technical note presents a comprehensive approach to understanding the impact of Generative AI (GAI) technologies on the workforce based on skills. It outlines a technical framework and methodology aligned with the latest literature, composed of three stages:

- 1. GAI-assisted skill classification
- 2. Embedding-driven skill classification expansion
- 3. Skill-based occupation classification

Intuitively, this methodology leads to an assignment of the extent to which each one of around 50,000 skills in Linkedln's skills taxonomy is replicable and complemented by GAI, and uses these scores as well as the extent to which each of those skills is important for a given occupation to create a composite score along each dimension for each occupation. These composite scores are used to classify each occupation into one of three groups: Augmented, Disrupted, or Insulated from GAI. External validation against scholarly exposure scores highlights correlations with existing literature, providing insights into the robustness of the proposed approach.

Introduction

Understanding the impact of Generative AI (GAI) technologies on the workforce is crucial for navigating its integration into the economy. Artificial Intelligence (AI) encompasses technologies that simulate human intelligence, such as learning, reasoning, and problem-solving, in machines. GAI specifically focuses on machines generating new content, like text, images, or code, based on patterns learned from vast datasets. Examples of GAI tools include Copilot, GitHub Copilot, and ChatGPT.

This technical note proposes a framework and a methodology to describe and model the potential and observed impact of GAI on occupation, and thereby on workers, based on skills. Economic literature has traditionally defined occupations as bundles of tasks (Acemoglu & Autor, 2010), but in the era of the knowledge economy, academics and practitioners are increasingly redefining occupations as bundles of skills (Bennett et al., 2022; E. W. Felten et al., 2018).

LinkedIn members can self-report their skills by adding them to their profiles, and employers can specify which skills they are looking for in job postings. As a result, LinkedIn has one of the richest skill taxonomies in the world (Macskássy et al., 2023), updated daily by members and employers, and structured and maintained by a team of specialized taxonomists and linguists. The work described in this note leverages LinkedIn's skills taxonomy, and particularly skills explicitly added by

members to their profiles,¹ along with the latest literature on Al and the future of work, to measure the extent to which GAI, in particular, stands to change work.

In doing so, we consider two concepts following the literature:

- GAI-replicability: This concept denotes the extent to which GAI technologies can
 proficiently execute a skill. Skills falling under this category are those that GAI can replicate
 effectively. Examples of such skills include text generation, language translation, and image
 generation.
- 2. GAl-complementarity: In contrast, skills categorized as GAl-complementary are those that remain challenging for GAI to perform independently, thus relying on human input or collaboration. These skills represent areas where human expertise remains indispensable, at least for the foreseeable future. Examples include leadership, creativity in problem-solving, and emotional intelligence.

The 3-staged methodology below explains the methodology followed to classify the extent to which skills in LinkedIn's taxonomy are GAI-replicable and/or GAI-complementary, and how we can apply these scores to classify occupations.

Methodology

Stage 1: GAI-assisted skill classification

To delineate GAI-replicable and GAI-complementary skills, we initiate the process by querying ChatGPT (first done in February 2023 using ChatGTP 3.5) with specific prompts:

- 1. **GAI-replicable skills:** "What are the 100 top skills that AI technologies (ChatGPT, Dall-E, LaMDA, etc.) can perform very well?"
- 2. GAI-complementary skills: "What are the 100 top skills that can currently exclusively be performed by humans?"

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¹ Linkedln's data counts with three types of data sources for skills: (i) explicit: those explicitly added by members to their profiles or required by employers in job postings, (ii) implicit: those extracted from the member profile or job posting text without having been explicitly added as skills, and (iii) inferred: those derived from machine learning models. This work uses explicit skills exclusively.

Note that the queries were repeated using ChatGPT 4.0 in March 2024, resulting in a very similar list, which reflects that the original list captures the great majority of the technological effect of these tools at the time this technical note was published (April, 2024). Examples of GAI-replicable skills from this process include resume writing, evolutionary algorithms, and image restoration. Examples of GAI-complementary human skills include project management, conflict resolution, and software innovation.

Subsequently, we align the generated skill lists with LinkedIn's comprehensive skills taxonomy using the LinkedIn taxonomy API. To ensure accuracy, we further refine the matches through manual curation. This process performed in February 2023 resulted in the classification of 1,200 skills as either GAI-replicable or GAI-complementary. Two separate random samples (sizes 10% each) were manually reviewed and curated by data scientists with skills specialization. Based on learnings from the manual review, we further curate skills in popular skill groups.

Stage 2: Embedding-driven skill classification expansion

While Stage 1 initially categorized over one thousand skills, this represents only a fraction of the nearly fifty thousand skills available in the Linkedln taxonomy. To compensate for this gap, we expand our coverage by employing <u>skill embedding</u>-based similarities to extend the skill classification beyond those identified in Stage 1 to encompass the entire taxonomy.

The embedding-driven skill classification expansion is performed in the following way:

The objective is to assign each $skill_i$ a GAI-replicability score s_i^r and a GAI-complementary score s_i^c . Let σ_{ij} denote the embedding-based similarity score between $skill_i$ and $skill_j$, and let S represent the N_SxN_S similarity matrix with σ_{ij} as its i,j^{th} element. Additionally, let M_r be the set of skills from stage 1 which are classified as replicable by GAI, and M_c be the set skills from stage 1 which are classified as complementary to GAI.

We compute the scores \hat{s}_i^r and \hat{s}_i^c using the following steps:

1. We calculate the similarity between every pair of skills using skill embeddings, resulting in the matrix S. It is important to note that skill embedding similarities are scores derived from LLM models based on context co-occurrence.²

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² Skill embeddings refer to a technique used to represent skills in a high-dimensional vector space. These embeddings capture the semantic relationships between different skills based on how they co-occur in profiles, job postings, or other textual data within the LinkedIn ecosystem (Yan et al., 2023).

- 2. For any given $skill_i$ not classified by stage 1, we examine the vector of similarity scores between $skill_i$ and stage-1 classified GAI-replicable skills. We select the maximum similar score from the vector as $skill_i$'s probabilistic GAI-replicability score. i.e., $s_i^r = \max_{j \in M_r} \{\sigma_{ij}\}$.
- 3. We repeat step 2 for GAI-complementary scores, i.e. $s_i^c = \max_{j \in M_c} \{\sigma_{ij}\}$.
- 4. Subsequently, given the scores follow a distribution close to Normal, we classify each skill as GAI-replicable if its replicable score is above the average score, i.e. $\hat{s}_i^r = 1 \left(s_i^r > \frac{1}{N} \sum_{\forall j} s_j^r \right)$, and each skill as GAI-complementary if its complementary score exceeds the mean: $\hat{s}_i^c = 1 \left(s_i^c > \frac{1}{N} \sum_{\forall j} s_j^c \right)$.

As a result, a skill may be classified as replicable (\hat{s}_i^r =1), complementary (\hat{s}_i^c =1), both, or neither. A few examples of this process helps illustrate the logic. Take the skill "workplace relationships". This is not a skill scored in stage 1. However, it has the closest similarity score among GAI-complementary skills from stage 1 to "conflict resolution" (similarity score of 0.87), which gives this skill a high weight for GAI complementarity. Another example is the skill of "cover letters", which has as its most similar score among GAI replicable skills "resume writing" (similarity score of 0.90). Thus, cover letters skill receives that score (0.90) for GAI-replicability.

Stage 3: Skill-based occupation classification

For each occupation, we calculate the percentage of skills that are GAI-replicable and GAI-complementary based on each occupations' <u>skills genome</u>. An occupation's skills genome is the ranking of its top most relevant skills, based on a TF-IDF model. In this model, skills are relevant when they tend to be disproportionately added by members in this occupation compared to members in other occupations.

Let $TFIDF_{ki}$ be the TF-IDF score of skill i in occupation k, and θ_k be the set of top 100 skills for occupation k (those with the 100-highest TF-IDF scores). Then, occupation o's GAI-replicability score is given by $o_k^r = \sum_{i \in \theta_k} \frac{TFIDF_{ki} \times \hat{s}_i^r}{TFIDF_{ki}}$. Intuitively, the score is a weighted average of what fraction of its top skills are GAI-replicable, weighted by the importance of that skill to that occupation. An occupation's GAI-complementary score is similarly given by $o_k^c = \sum_{i \in \theta_k} \frac{TFIDF_{ki} \times \hat{s}_i^c}{TFIDF_{ki}}$. Given it is a weighted average of binary variables, o_k^r and o_k^c range from zero to one, and may loosely be interpreted as the normalized fraction of its skills which are GAI-replicable and GAI-complementary, respectively. Given the procedure described above (in particular, in

Stage 2), it is not necessarily the case that $o_k^r + o_k^c \le 1$. Indeed, both scores may be above 0.5 and yield a total score which is greater than one.

As a result, each occupation o_k is associated with a GAI-replicability score o_k^r and a GAI-complementarity score o_k^c . We then proceed to classify each occupation into one of three GAI classifications: Augmented, Disrupted, or Insulated from GAI, based on their GAI-replicable and GAI-complementary medians:

- $o_k^r > median(o_k^r)$ and $o_k^c > median(o_k^c)$: occupation k is classified as Augmented.
- $o_k^r > median(o_k^r)$ and $o_k^c \leq median(o_k^c)$: occupation k is classified as D is D i
- $o_k^r \leq median(o_k^r)$: occupation k is classified as *Insulated*.

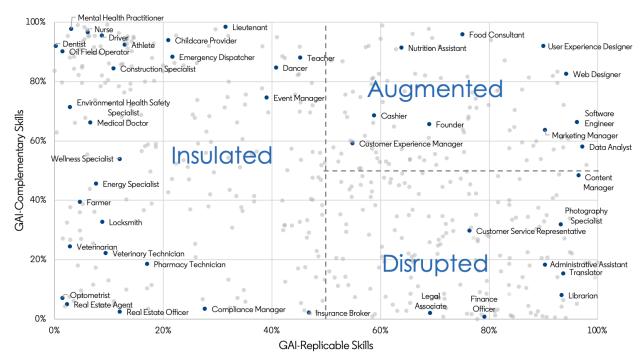
These thresholds and names were selected primarily to ensure simplicity and ease of understanding for users. By opting for straightforward criteria and clear categorizations, the classification process aims to be accessible and intuitive, facilitating effective interpretation and decision-making.

Consider how this concept applies to various occupations. Take software engineers, for instance. Their top skills, including Git and Software Development, are identified as both GAI-replicable and GAI-complementary. Based on the skill embedding analysis, Software Development skill is most similar to XML, a GAI-replicable skill, and Software Innovation, a GAI-complementary skill. This dual classification that occurs with its other top skills suggests that their profession is likely to be augmented by GAI, based on the weighted average of their skills.

Alternatively, consider teachers; while they have some skills which are rated as GAI-replicable (such as lesson planning and curriculum development, which are also classified as GAI-complemented), many of their top skills are classified only as GAI-complemented, including classroom management, educational leadership. Based on these scores, teachers are classified as being in an insulated occupation.

Finally, consider administrative assistants. Unlike the previous examples, their skills don't include any that are classified as GAI-complemented in the top ten skills. Instead, the top skills it has are classified as replicable by GAI, including ones such as data entry, calendaring, and travel arrangements. Based on these and the other scores, administrative assistants are classified as being in an occupation potentially disrupted by GAI.

Final results are reflected in a research note called <u>Preparing the Workforce for Generative Al</u> (Kimbrough & Carpanelli, 2023). The following figure, replicated from Kimbrough and Carpanelli (2023), illustrates the stage 3 process assigning each occupation to a GAI-classification group.

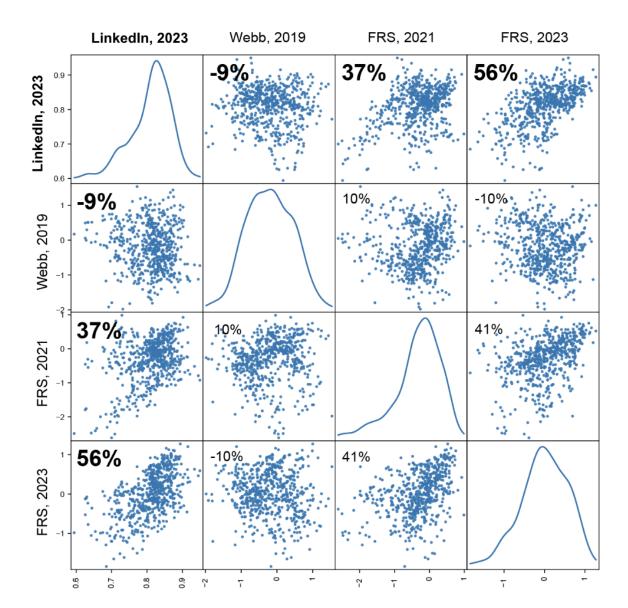


Note: replicated from Exhibit 3 of Kimbrough and Carpanelli (2023).

Validation

For external validation, we ingest and align several exposure scores from academic sources, including Webb (Webb, 2019), FRS 2021 (E. Felten et al., 2021), and FRS 2023 (E. W. Felten et al., 2023). The LinkedIn GAI-replicability score o_k^r , akin to a GAI-exposure metric, exhibits a negative correlation with Webb's AI exposure score – which is not surprising given Webb's is a general AI exposure metric designed before the mainstream emergence and diffusion of GAI. Conversely, it demonstrates a positive correlation with FRS 2021's AI exposure score (37%) and FRS's GAI exposure score (56%). It's noteworthy that the highest positive correlation emerges when compared against the sole GAI-specific metric, and that FSR GAI exposure scores are also negatively correlated with Webb's scores. However, it's essential to interpret these correlations cautiously, given their reliance on nuanced taxonomy crosswalks.

Further validation against newer literature (Eloundou et al., 2023) is yet to be performed, but the pertinent data were unavailable at the time of this technical note (April 2024).



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