WorldBank Assignment

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Abstract

This study evaluates how AI affects Filipino jobs found in My Career Advisor (MCA). The occupations were mapped to the Standard Occupational Classification (SOC) codes of the O*NET database via PSOC and ISCO crosswalks. To measure the effects of AI, the AI Occupational Exposure (AIOE) and complementarity index were computed following Felten et al. (2021) and Pizzinelli et al. (2023), with 16.9% of values imputed. Jobs were classified into four types: Augmentable, Automatable, Protected, and Isolated. Higher-educated workers hold 46% of Augmentable jobs versus 8% for less-educated, while 43% of less-educated jobs are Isolated. Sector-level C-AIOE analysis shows financial services, administrative support, and ICT face the highest AI exposure, whereas construction, agriculture, and manufacturing are lowest. These findings highlight heterogeneous AI risks across sectors and educational pathways, offering insights for workforce planning.

1 Crosswalk MCA Jobs with SOC Codes

The Excel file FINAL (WIP)-MCA Job list August 2025.xlsx[1] contains two relevant sheets:

1. **USE_final**, which holds the final list of jobs, and
2. **Pass 3 - Sector reports**, which contains a tentative list of jobs with their corresponding PSOC codes.

Notably, the jobs in the final MCA list do not initially have a corresponding SOC code, which is required to link the AIOE and complementarity scores. However, we noticed that the Jaccard index between the two lists aforementioned exceeds 97%, indicating substantial overlap. Therefore, we merged the two sheets to ensure that the majority of jobs in the final list were assigned a PSOC code, which could eventually be mapped to a SOC code.

During this process, 22 jobs were lost in the mapping from job titles to PSOC codes, which were subsequently crosswalked to the 2008 ISCO codes. During the mapping of ISCO codes to SOC codes[2], an additional 25 jobs were lost. In total, 47 jobs were dropped in the entire process of mapping the MCA job list to SOC codes. As shown in Figure 1, the majority of jobs are retained however through the mapping stages.

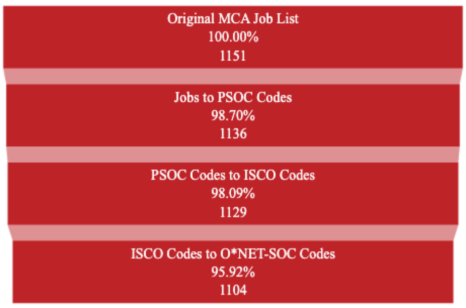

Figure 1: Funnel chart showing from MCA jobs to SOC codes.

Because only a small amount of jobs were unmatched, ChatGPT was used to suggest suitable SOC codes. A full record of this process is available here: Job to SOC code mapping. Given now that each job in the MCA list has

[1] For internal use, see the MCA Job List Mapping

[2] See the ISCO-08 x SOC 2010 Crosswalk provided by the Bureau of Labor Statistics.

their corresponding SOC code, we can start determining their AIOE and complementarity scores.

2 Assign AIOE Scores to SOC Codes

Felten et al. (2021) introduced the AIOE measure by linking ten AI applications to 52 O*NET abilities, using crowd-sourced relevance ratings to capture how strongly each application relates to a given ability. Summing these ratings yields an ability-level exposure score, A_j, where j indexes the 52 abilities.

Each job in O*NET also has ratings for how important and prevalent an ability is, denoted by I_{jk} and L_{jk} for job k. Since a job is essentially a weighted bundle of abilities, Felten et al. aggregate across them using $\sum_{j=1}^{52} L_{jk} \cdot I_{jk}$. To incorporate AI, they multiply by A_j to capture how exposed each ability is to AI before summing across all abilities. The AIOE for some job k is then:

$$\text{AIOE}_k = \frac{\sum_{j=1}^{52} A_j \cdot L_{jk} \cdot I_{jk}}{\sum_{j=1}^{52} L_{jk} \cdot I_{jk}}.$$

We validated our implementation by comparing our distribution of AIOE scores with the histogram reported by Felten et al. as done in Figure 2. While small differences arose from updated O*NET ratings, the overall shapes were consistent, suggesting fidelity to the original methodology.

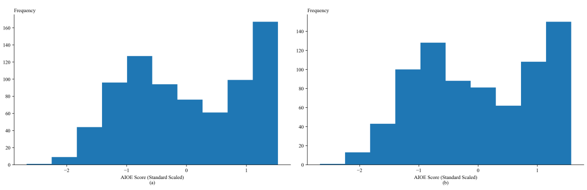

Figure 2: Histograms of AIOE Scores by Felten et al. (a) and by Viray and Oximas (b)

Some SOC codes did not directly map due to legacy classifications and were manually updated. Even after accounting for legacy codes, roughly 16.9% of jobs lacked AIOE values, which we imputed using the median AIOE of their major-minor SOC group to account for the left-skewed distribution.

3 Assign Complementarity Scores to SOC Codes

Pizzinelli et al. (2023) extend the AIOE framework with a *complementarity index* that measures how much AI supports rather than substitutes human labor. The index uses 11 O*NET work context variables (scored 0–100 by importance or frequency) and Job Zone (ordinal 1–5, rescaled to 0–100), grouped into six dimensions:

1. **Communication** – Face-to-Face Discussions, Public Speaking;
2. **Responsibility** – Responsibility for Outcomes, Responsibility for Others' Health;
3. **Physical Conditions** – Outdoor Environments, Physical Proximity;
4. **Criticality** – Consequence of Errors, Freedom of Decisions, Frequency of Decisions;
5. **Routine** – Degree of Automation (inverted to "Degree of Freedom")[3], Structured vs. Unstructured Work; and
6. **Skills** – Job Zone (scaled from 1 = least preparation to 5 = most preparation).

Each dimension score is the mean of its components, and the overall index is the mean across all six. To interpret complementarity, as the score of any dimension increases, AI is more likely to augment labor, and thus the complementarity index also increases.

To verify the consistency of our methodology, we compared the correlation matrix of the six computed dimensions with the corresponding matrix reported in the study. Since the pairwise correlations in our results closely align with those presented by Pizzinelli et al. as shown in Figure 3, we can reasonably conclude that our implementation of the methodology is correct.

Similar to assigning the AIOE, some SOC codes did not get a complementarity score because of legacy classifications. Even after accounting for legacy codes, roughly 16.9% of

[3] The inversion is defined as Degree of Freedom = 100 − Degree of Automation. This ensures that higher Degree of Freedom values reflect greater AI complementarity.

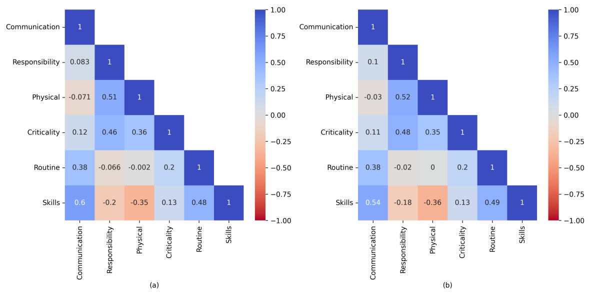

Figure 3: Correlation Matrices by Pizzinelli et al. (a) and by Viray and Oximas (b)

jobs lacked complementarity scores, which we imputed using the mean score of their major-minor SOC group.

4 Analyze Data

Since we now have the AIOE and complementarity scores, let us explore the data by looking at the labor supply and demand.

4.1 Defining the 2-by-2 Framework

We classified each job in the MCA dataset using its AI Occupational Exposure (AIOE) and complementarity scores. Jobs with below-median AIOE were categorized as *Low Exposure*, while those with above-median AIOE were considered *High Exposure*. Within each exposure group, jobs were further subdivided based on whether their complementarity score fell below or above the overall median.

This framework produces four job types. Low-exposure jobs are either *Protected* (high complementarity) or *Isolated* (low complementarity). High-exposure jobs are either *Augmentable* (high complementarity) or *Automatable* (low complementarity). This is summarized in Figure 4

By organizing the labor market in this way, the challenge shifts from one of job security (whether a job will be replaced) to one of skills preparation, emphasizing the need for workers to adapt to AI-intensive tasks.

4.2 Labor Supply

From the framework, we can now examine how labor supply differs between workers who pursued higher education and those who did

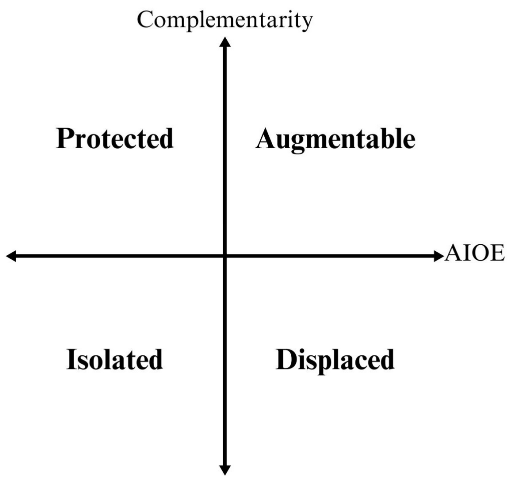

Figure 4: Matrix of 2-by-2 Framework

not. Table 1 shows that jobs held by higher-educated workers are disproportionately classified as Augmentable, meaning these roles are highly exposed to AI but also benefit from strong complementarities. In contrast, jobs held by less-educated workers are more likely to fall under the Isolated or Protected categories. The former face low complementarity and limited adaptability, while the latter remain shielded from AI because of their low exposure.

Classification	Higher Education	Not Higher Education
Augmentable	46%	8%
Protected	9%	35%
Isolated	12%	43%
Displaced	34%	15%

Table 1: Percentage of jobs by educational pathway and AI classification.

We further visualized this relationship using a scatterplot of AIOE against complementarity in Figure 5. To illustrate the four classifications, we added representative examples of jobs from the MCA dataset.

4.3 Labor Demand

To examine labor demand, we used a new metric called the C-AIOE to summarize the risk of replacement at the occupation level to AI. It is formally defined as:

$$\text{C-AIOE}_i = \text{AIOE}_i \cdot \big(1 - (\theta_i - \theta_{\text{MIN}})\big),$$

where i indexes the job, θ_i is complementarity to AI, and θ_{MIN} is minimum value of θ_i across

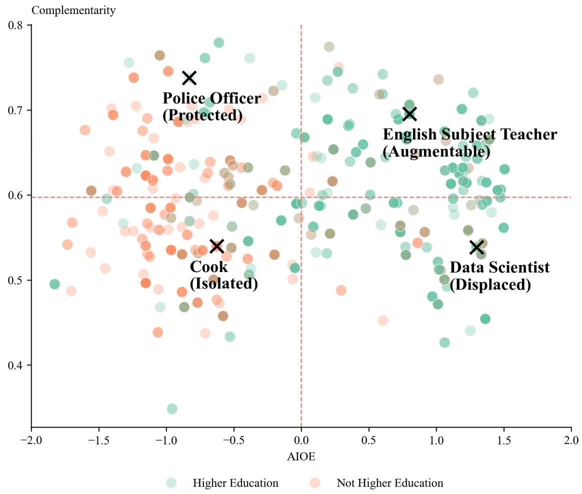

Figure 5: AIOE vs. Complementarity for Filipino Jobs by Educational Pathway

all occupations. Overall, jobs with higher C-AIOE (because of higher AIOE or lower complementarity) are more likely to face AI replacement.

This was then aggregated to each of the 21 job sectors by taking the mean C-AIOE of their respective jobs. Figure 6 plots the results, highlighting that jobs in financial services, administrative support, and ICT have the highest average risk, while construction, agriculture, and manufacturing face the lowest.

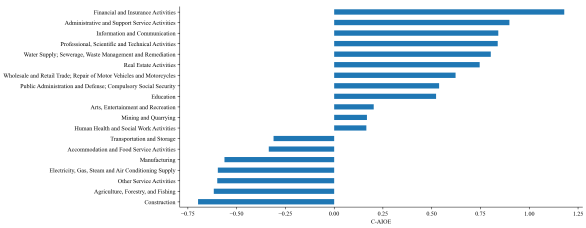

Figure 6: Job Sectors Ranked Most Likely Automated by AI (Based on C-AIOE)

5 Limitations and Recommendations

Based on the study, one key limitation is the reliance on a US-based dataset. Although the focus is on Filipino jobs, the AIOE and complementarity scores are derived from the O*NET database. This approach remains acceptable, as other studies, such as those by Cucio & Hennig (2025) and Gymrek (2024), have applied the same method to the Filipino and Latin American labor markets, respectively.

A recommendation for future research is to incorporate labor supply and demand by weighting results according to the quantity of jobs supplied and demanded. The current methodology relies only on the job list and does not account for whether these jobs are actually in demand.

References

Cucio, M. and Hennig, T. (2025). Artificial intelligence and the philippine labor market: Mapping occupational exposure and complementarity. IMF Working Paper 25/43, International Monetary Fund.

Felten, E., Raj, M., and Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12):2195–2217.

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