Navigating Workforce Transformation: AI Augmentation and Automation Risks Across Four Occupation Zones and Various Similarity Measures

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Introduction

Automation is transforming the labor market at an unprecedented pace, raising important questions about the future of work and the skills required to thrive in an increasingly automated world. For many workers, the rise of automation brings both hope and fear—concerns about job security, the need for upskilling, and whether their current skills will remain relevant. As Frey and Osborne (2017) highlight, computerized automation, often driven by rule-based, repetitive tasks, tends to displace workers, particularly those performing routine and predictable tasks. In contrast, Felten et al. (2023) emphasize AI-driven automation powered by large language models (LLMs), which complement human capabilities and enhance cognitive, non-routine, and creative tasks.

Understanding these two distinct types of automation is not just academic—it's essential for everyday workers who want to prepare for the future. The current wave of automation isn't only about whether jobs will exist in the future, but how those jobs will change, what skills will be required, and who stands to benefit from these shifts. By examining the differences between FO (Frey & Osborne, 2017) and FRS (Felten et al., 2023) measures of automation, we can better identify which types of occupations are at greater risk of displacement and which are more likely to experience opportunities for upskilling.

One of the key challenges in understanding the automation-driven labor market is recognizing how task similarities shape these outcomes. Many might assume that if two occupations share similar tasks, upskilling opportunities are more likely. However, as Frey and Osborne (2017) argue, increased task similarity often means higher automation risk, reducing the need for skill development in already automatable tasks. On the other hand, Felten et al. (2023) show that AI-driven automation enhances higher-level cognitive tasks, leading to new opportunities for upskilling, especially in non-routine, knowledge-intensive jobs.

For workers and policymakers alike, understanding these automation dynamics is crucial. If workers' tasks are highly routine and susceptible to FO automation, they may face fewer upskilling opportunities as their tasks are replaced by machines. Conversely, workers in knowledge-intensive jobs that benefit from AI-driven automation are more likely to see their skillsets complement technological advancements, offering new opportunities for growth. Policymakers must recognize these differences to design targeted reskilling programs that address the specific needs of different worker types. By understanding how AI-driven automation

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complements human capabilities, we can help ensure that workers aren't left behind in the age of AI.

Ultimately, the current automation landscape is not just about whether jobs will exist but how they will evolve. By examining the differences between FO and FRS automation, and the relationship between task similarities and upskilling, we can better understand how to support workers who are at risk of displacement, while helping others unlock new pathways to career growth.

This study contributes uniquely to the existing literature by distinguishing between AI-driven augmentation and computerized automation risks, offering a more nuanced understanding of how automation impacts vary across different job zones. By introducing a four-occupation zone framework—AI Augmentation, Computerized Displacement, Displacement & Augmentation, and No Displacement No Augmentation zones—the study provides greater precision in identifying the distinct dynamics of automation and AI impacts. Additionally, its focus on occupation similarity and upskilling behavior extends the existing knowledge on labor market adaptability, emphasizing how task similarity influences automation risks and mobility patterns over time. Through heatmap and network analysis methodologies, the study offers a novel perspective on the distribution of automation risks, contributing to a deeper comprehension of how automation shapes workforce dynamics and policy implications.

Literature Review and Hypothesis

Computerized automation (Frey & Osborne, 2017, called FO hereafter) affects occupational upskilling opportunities differently than AI-powered automation enabled by large language models (LLMs) (Felten et al., 2023, called FRS hereafter). This paper argues that while FO disproportionately impacts routine jobs by devaluing skill requirements, FRS has a broader and more nuanced effect on skill transformation, enhancing cognitive and non-routine skills.

Frey and Osborne (2017) classify jobs into high and low susceptibility to automation based on task routineness. Occupations like assembly line work or clerical tasks—highly routine and predictable—are highly automatable. Digital automation reduces demand for human input, leading to skill devaluation or obsolescence in these roles. Balsmeier and Woerter (2019) corroborate this by demonstrating that routine-intensive tasks experience job displacement. However, they also note that complementary industries can generate higher-skill demands, creating a dual impact depending on the sector.

Felten et al. (2023) emphasize that AI-powered LLMs influence skill development differently. These models augment human cognitive capabilities by providing real-time access to knowledge, aiding creative and analytical tasks. For instance, knowledge workers—such as analysts or writers—leverage AI for synthesizing complex information, allowing upskilling in areas requiring critical thinking and problem-solving. Brynjolfsson, Rock, and Syverson (2021) highlight how AI complements intangible assets like innovation, further fostering productivity and skill growth in knowledge-intensive roles.

The divergence between FO and FRS lies in their task-specific impacts. FO predominantly targets predictable and routine tasks, while FRS influences knowledge-intensive and creative domains. This aligns with findings from Autor and Salomons (2018), who note that automation's overall impact depends on the degree of complementarity between technology and human labor. Unlike FO, which often leads to displacement, FRS facilitates skill augmentation by enabling workers to engage in higher-order tasks that are less susceptible to automation.

Computerized automation and AI LLM automation present distinct pathways for skill evolution in the workforce. FO's primary effect is on devaluing and displacing routine tasks, whereas FRS enhances cognitive and creative capabilities. These differences underscore the need for tailored policy interventions to address sector-specific impacts and ensure equitable skill development opportunities. We therefore hypothesize:

> H1: Computerized automation (Frey & Osborne, 2017, called FO here after) affects occupation upskill opportunities different from AI LLM automation (Felten et al., 2023, called FRS hereafter).

Computerized automation, as outlined by Frey and Osborne (2017), refers to rule-based, repetitive tasks typically automated using predefined programming and machinery. Such tasks often involve routine cognitive or manual activities, where the likelihood of displacement is high because the technology efficiently substitutes labor. By contrast, AI-driven automation, particularly involving LLMs, leverages machine learning to perform tasks requiring cognitive flexibility, complex decision-making, and natural language processing, as discussed by Felten et al. (2023).

Occupations with high AI impact (high FRS scores) but low computerized displacement risks (low FO scores) are positioned for upskilling opportunities because AI complements rather than replaces human capabilities. Felten et al. (2023) emphasize that these jobs typically require problem-solving, creativity, and collaboration—skills enhanced rather than supplanted by AI. Examples include roles in education, healthcare, and creative industries where AI tools can augment human decision-making and efficiency.

Supporting this, Bessen (2019) argues that technological advancements often lead to skill augmentation rather than displacement in tasks requiring adaptability. For instance, educators using AI-based tools like LLMs can better personalize learning experiences without being displaced, as AI aids rather than replaces their core responsibilities.

In contrast, occupations with high computerized displacement risks (high FO scores) are least likely to upskill because these roles are predominantly routine and standardized, making them more vulnerable to full automation. Frey and Osborne (2017) classify such roles as those in manufacturing, clerical work, and other repetitive sectors. Once displaced, these roles provide limited pathways for skill enhancement, as displaced workers often require entirely new skillsets to transition to other industries.

Acemoglu and Restrepo (2020) highlight the "displacement effect," where technology adoption in routine tasks often leads to a net reduction in employment opportunities without significant investments in reskilling infrastructure. This reinforces the notion that high computerized displacement risks impede upskilling efforts.

The divergence in upskilling potential arises from the nature of automation's impact:

1. **AI-driven automation** (high FRS, low FO): Enhances cognitive capabilities, enabling workers to adapt and upskill in complementary roles (Felten et al., 2023; Bessen, 2019).
2. **Computerized automation** (high FO): Displaces routine work without offering avenues for augmentation, as the tasks themselves are fully automatable (Frey & Osborne, 2017).

The potential for upskilling depends on the interplay between the nature of tasks and the type of automation applied. Occupations with high AI impact but low computerized displacement risks are poised for skill enhancement because AI acts as a complement rather than a substitute. Conversely, jobs susceptible to computerized displacement are less likely to foster upskilling, as automation wholly replaces human labor in these contexts. These findings, grounded in robust studies and literature, highlight the critical role of task characteristics in shaping the future of work. We therefore hypothesize

> H2: Due to different nature of automation between computerized automation and AI LLM automation, occupations with high AI impact (high FRS measure effect) and low computerized displacement risks (low FO measure effect) are most likely to up skill, while occupations with the high computerized displacement risk (high FO measure effect) and least likely to upskill.

Computerized automation typically focuses on executing well-defined, repetitive, and rule-based tasks with precision and consistency. This kind of automation often leads to **task displacement**, particularly for low-skill routine jobs (Frey & Osborne, 2017). In contrast, AI LLM automation, driven by advancements in generative models and machine learning, excels in tasks involving language comprehension, reasoning, and content generation. These tasks include **creative problem-solving** and **cognitive augmentation**, often associated with higher-skill professions (Felten et al., 2023). Those two different measures result in different effects on four occupation types:

1. High AI Impact, Low FO Impact: These occupations, such as marketing specialists or HR professionals, benefit significantly from AI-driven tools that augment productivity without fully replacing workers. For instance, LLMs assist in writing reports, analyzing trends, and drafting communication. Research suggests these roles see increased demand for upskilling in using AI tools to stay competitive, as noted by Felten et al. (2023), who highlight that such tasks require integration of AI capabilities rather than replacement.

2. High AI Impact, High FO Impact: Occupations like customer support or legal assistants are heavily impacted by both automation types. While FO automation may replace repetitive components, AI LLMs enhance efficiency in high-level tasks such as summarizing legal documents or conducting sentiment analysis (Brynjolfsson et al., 2018). Upskilling in these roles focuses on AI tool proficiency and developing skills that complement AI, such as ethical judgment and decision-making.

3. Low AI Impact, Low FO Impact: Manual labor-intensive jobs, such as janitorial work, remain relatively insulated from both automation types. Upskilling opportunities in these roles are traditionally limited; however, AI may influence managerial aspects of such roles, like predictive maintenance scheduling, requiring basic digital literacy (Arntz et al., 2016).

4. Low. AI Impact, High FO Impact: Routine-intensive clerical jobs, such as data entry, are highly susceptible to displacement from computerized automation but face limited AI augmentation. Arntz et al. (2016) argue that these roles see minimal upskilling opportunities, as FO automation replaces rather than enhances tasks.

In earlier decades, computerized automation emphasized standardization and efficiency. This phase spurred demand for reskilling into non-routine cognitive and social-interactive tasks (Autor et al., 2003). Upskilling trends were uneven, with limited opportunities for routine-intensive jobs. We can call this computerized automation era.

As LLMs become prevalent, occupations involving creativity and analytical thinking gain new upskilling avenues. Felten et al. (2023) emphasize how AI empowers professionals by handling tedious cognitive loads, fostering opportunities for skill diversification. Upskilling now focuses on AI literacy, ethical AI management, and soft skills, ensuring effective human-AI collaboration. We can call this AI LLM automation era.

The distinct nature of computerized automation and AI LLM automation has created divergent upskilling trajectories for the four occupational types. While FO automation largely displaces routine work, AI LLM automation enables augmentation of high-skill roles and necessitates adaptation through upskilling. By understanding these trends, workers and policymakers can better prepare for the future of work, ensuring equitable opportunities for skill development across all sectors. We therefore hypothesize:

> H3: Due to different nature of automation between computerized automation and AI LLM automation, the four occupation types face different upskill opportunity trends over the years.

In terms of the pathway for upskilling, people might often think it is easier to upskill from similar occupations. To explain the relationship between occupation similarities and upskill odds, we need to draw on concepts from the literature, focusing on detailed tasks, broad tasks, domain knowledge, and technical skills. Various studies highlight the distinction between how occupation similarities can impact skills requirements and how these relationships might not always translate directly into upskilling odds.

Detailed task similarity refers to the overlap in specific, narrowly-defined tasks that two occupations perform. Frey and Osborne (2017) argue that as occupations become more similar in their detailed tasks, the likelihood of technological substitution increases. However, this does not necessarily imply that there will be an equal probability of upskilling. Frey and Osborne (2017) argue that jobs with high task similarity are more susceptible to automation, reducing the need for new skill development due to the efficiency gained through technological substitution (Frey & Osborne, 2017). For example, if two occupations share many similar tasks such as routine data processing or manual labor, automation may replace these tasks, reducing the need for workers to reskill. However, this does not necessarily imply that these occupations' upskilling odds will increase. Instead, workers may become displaced due to automation, leading to lower upskilling needs for tasks that are no longer required.

Broad task similarity refers to more general categories of tasks that are performed across different occupations. Felten et al. (2023) highlight that occupations with higher broad task similarities often rely on shared foundational skills and knowledge. While this might suggest greater overlap in job roles, it does not always correlate with higher upskill odds. Felten et al. (2023) assert that broader task similarities might indicate reduced job specialization, which can limit the need for specific skill upgrades as automation focuses on these generalized task categories. For instance, occupations that rely on tasks involving customer service or administrative roles might show high broad task similarity. However, because these tasks tend to be less technical, technological advancements might not necessarily drive high upskilling needs, particularly in non-technical roles where automation can substitute for human labor (Felten et al., 2023).

Domain knowledge refers to the understanding of specialized content related to a particular field, whereas technical skills refer to the application of specific technologies or tools. According to Felten et al. (2023), occupations with high domain knowledge and technical skill overlap may show higher upskilling odds since technical skills are often tied to the use of new technologies. However, Frey and Osborne (2017) point out that even when technical skills overlap, upskilling odds may not always follow because automation can reduce the demand for such skills in routine or highly standardized tasks. For example, technical roles such as software development often show high technical skill similarity due to overlapping requirements like coding or software development tools. However, if automation or artificial intelligence (AI) can perform these tasks, the need for workers to continuously upskill might decrease, particularly if these technical roles are heavily automated. Therefore, higher technical skill overlap does not necessarily lead to increased upskilling needs if automation displaces the technical tasks themselves (Frey & Osborne, 2017).

From the detailed and broad task similarities, and considering domain knowledge and technical skills overlap, higher occupation similarities often suggest a potential for automation rather than an increased demand for upskilling. Frey and Osborne (2017) point to automation as a driving force behind reduced upskilling odds, especially when similar tasks become automated. Meanwhile, Felten et al. (2023) underline that high technical skill similarity can persist but may not necessarily translate to increased upskilling, particularly in roles susceptible to automation. Thus, occupation similarities do not guarantee higher upskill odds in all cases. We therefore hypothesize:

H4: Higher occupation similarities do not necessarily relate to higher upskill odds.

Methodology

Occupational Similarity Indices

A critical component of the study is the development of indices of occupational similarity, which capture the alignment of tasks, technology skills, and knowledge domain expertise between occupations. The rationale for selecting these occupational attributes follows closely from Christenko (2022) although we add technology skills given their relevance in an automation/computerization context. We use these indices to explain occupational transitions through regression analysis. As a basis for creating and operationalizing the indices, we draw upon the U.S. Department of Labor's Standard Occupational Classification (SOC) Network and the O*NET database, which provides detailed information on 923 occupations and their attributes. We use the 2022 occupation data, scaling all indices from 0 to 1, with higher values indicating greater similarity between occupations.

Cosine on Detailed Task:

The O*NET database includes detailed text descriptions of tasks associated with each occupation. There are 16,850 unique task descriptions in the 2022 data. Examples include tasks such as "Direct or coordinate an organization's financial or budget activities to fund operations, maximize investments, or increase efficiency."

We apply text mining to these descriptions to construct an index of occupational similarity.First, we process and clean the task descriptions by removing stop words (e.g., "the," "and"), punctuation, and other irrelevant features. Then use Term Frequency-Inverse Document Frequency (TF-IDF) to identify words of high relevance, emphasizing terms unique to each occupation while minimizing the effects of common terms to multiple occupations. This approach is well-suited for sparse datasets like ours, where relatively few words describe each occupation. Cosine similarity scores are calculated for each pair of occupations based on their extracted words (using 1-gram tokens).

Task descriptions alone do not fully capture the importance of tasks or the technical and knowledge-based requirements specific to each occupation. To address this issue, we construct three additional indices using Manhattan distances applied to O*NET ratings of the importance of different occupational requirements. Manhattan distance is the sum of the absolute differences between the values of corresponding variables across two observations. It is a more suitable measure of distance than other metrics (such as Euclidean distance) when the variables are all on the same scale, which is the case for the O*NET ratings. Specifically, they range as they range from 1 (not very important) to 5 (very important). Given that Manhattan distance captures dissimilarity (i.e., a higher value indicates greater dissimilarity), we normalized the distances from 0 to 1 and flipped them such that a higher value indicates greater similarity. This also makes the indices compatible with the cosine similarity indices. Each index is described below:

Normalized Broad Task Similarity:

This index is ultimately based on O*NET importance ratings for Activities (elements), which capture tasks at a very coarse level. The reason we construct this index is because the detailed tasks do not indicate anything about their importance to different occupations. Additionally, since the detailed tasks do not have importance ratings, we have to go through a sequence of steps to convert the detailed tasks to the elements in the activities data.

We first use the Domain Word Association (DWA) crosswalk to convert the detailed tasks to DWA tasks, which provide broader conceptualizations of the tasks. For example, the detailed task "Review and analyze legislation, laws, or public policy and recommend changes to promote or support interests of the general population or special groups" is converted to the DWA task "Analyze impact of legal or regulatory changes." We then convert DWA to Inter-Word Association (IWA) tasks and ultimately to the Element name corresponding to broad activities. Following with the same example, the DWA task is converted to "Assess characteristics or impacts of regulations or policies, which in tun is converted to the Element name "Analyzing Data Information." We exploit the importance ratings corresponding with the elements for the Manhattan distance calculation. However, since the same element can show up more than once for any given occupation, we first take the average of the importance scores for each of the occupations and elements.

Normalized Domain Knowledge Similarity:

This index captures the domain knowledge required for an occupation. Two occupations may share similar tasks but require expertise in different fields. For example, post-secondary sociology and psychology teachers both engage in instruction and research but require distinct disciplinary backgrounds. O*NET identifies 33 knowledge categories, such as administrative management, transportation, and sociology/anthropology.

Normalized Technical Skill Similarity:

This index focuses on technology skills, specifically software-related competencies, rather than tools. Examples include accounting software, geographic information systems, and network security or VPN software.

Heatmap Visualization of Occupational Similarity

We use heatmaps to visualize the similarity within and between different occupational categories for each worker's Year 2 versus Year 1 occupations. To generate the heatmaps, we apply the similarity indices to the detailed 2022 O*NET occupational data and then calculate average similarity values both within and across major occupational groups (2-digit codes). In the heatmaps (Figures 1a-1d), red represents higher similarity, while green indicates lower similarity. We also include descriptive statistics for each set of averages to help in drawing meaningful conclusions from the maps. However, it is important to note that the statistics for the cosine similarity index are not directly comparable to those derived from the Manhattan distance, as they are based on different mathematical foundations.

Empirical Tests

The current study leverages individual-level data derived from the U.S. Current Population Survey (CPS) to examine job transitions from year 1 (2009–2022) to year 2 (2010–2023). Specifically, the dependent variable is measured as *Upskill, No Change,* and *Downskill*, reflecting transitions in occupational skill levels. To measure the marginal variable effects on the dependent variable, we adopted binomial logit models, shown as follows:

$$\Pr(\text{Upskill}_i = j) = \frac{\exp(\alpha_j + \beta_1 \text{Occupation Type}_i + \beta_2 \text{Similarity}_i + \beta_3 \text{FO Index}_i + \beta_4 \text{FRS Index}_i + \beta_5 \text{Control Variables}_i + \beta_6 \text{FE}_i)}{\sum_k \exp(\alpha_k + \beta_1 \text{Occupation Type}_i + \beta_2 \text{Similarity}_i + \beta_3 \text{FO Index}_i + \beta_4 \text{FRS Index}_i + \beta_5 \text{Control Variables}_i + \beta_6 \text{FE}_i)}$$

Where:

- **Upskill** is the dependent variable with three outcomes: **Upskilled** versus **De-skilled**.
- **Occupation Type** is a categorical variable representing the four automation-based zones.
- **Similarity** includes four different similarity indices: detailed task similarity, broad task similarity, domain knowledge similarity, and technical skill similarity.
- **FO Index** and **FRS Index** represent the computerized automation and AI/LLM automation risks, respectively.
- **Control Variables** include age, gender, race, ethnicity, marital status, education, health, and year of migration.
- **FE** denotes fixed effects (occupation, time, and location fixed effects).

Quadratic form of all the four similarity measures, as well as the FRS and FO indices, are adopted to capture the non-learn trends. We also adopted demeaned continuous variable measure to control for potential unobserved heterogeneity and mitigate issues of multicollinearity and endogeneity, providing a more precise estimation of the relationship between different occupation similarity measures, automation, and upskilling outcomes.

The relevant data are confined to years 2009-2023 after matching occupational similarity indices and automation probabilities (FO, FRS). Job transitions are categorized using the Department of Labor's (DOL) O*Net Job Zone framework, which groups occupations based on required educational attainment, related work experience, and on-the-job training (ONET Online, n.d.a). The study employs a binomial logit model to estimate the likelihood of job transitions between different Job Zones, which range from Job Zone 1 (low preparation) to Job Zone 5 (extensive preparation). The independent variables include occupational similarity/distance, worker demographics, regional effects, and year effects, along with interaction terms to capture potential moderating influences.

The ONET Job Zone framework, developed by the U.S. Department of Labor, categorizes occupations into five groups based on the preparation required, including education, work experience, and on-the-job training. Job Zone 1 requires little or no preparation, such as short-term training for roles like cashiers, while Job Zone 5 demands extensive preparation, often involving advanced degrees for positions such as surgeons or lawyers. Intermediate zones reflect increasing levels of preparation, ranging from moderate-term training (Job Zone 2) to bachelor's degrees and professional experience (Job Zone 4). This classification helps workers, employers, and policymakers assess the skills and education needed for various career paths (ONET Online, n.d.a). We therefore use the Job Zone level to represent upskill or downskill.

The Occupational Information Network (ONET) provides detailed descriptors for various job types, including manual and technical roles, as well as the associated skills and knowledge required. *Manual* jobs typically involve physical activities and tasks that require bodily movement and coordination, such as operating machinery or assembling products. *Technical* jobs, on the other hand, demand specialized knowledge and skills related to specific technologies or methodologies, often necessitating formal education or training in fields like engineering or information technology. *Broad skills* refer to general competencies that are applicable across multiple occupations, including critical thinking, problem-solving, and effective communication. *Knowledge* encompasses the organized sets of principles and facts that individuals apply within occupational contexts, such as understanding of mathematics, engineering principles, or customer service practices. These classifications assist in job analysis and career exploration by outlining the requirements and responsibilities associated with different occupations (ONET Online, n.d.b).

Findings

Descriptive stats

The FRS AI Displacement & Augmentation Risk Index (FRS Index) exhibits a moderate to strong positive correlation ($r = 0.5651$) with job zone upgrades, indicating that as job zones advance, the FRS Index increases. Conversely, the Computerization Automation and Job Displacement Risk Index (FO Index) shows a negative correlation ($r = -0.5439$) with job zone upgrades, suggesting that higher job zones are associated with lower FO Index values. Table X(b) illustrates this trend, with the FRS Index escalating alongside job zone upgrades, while the FO Index declines. Consequently, high job zone occupations, such as sociologists and management analysts, are positioned in the top-left quadrant of Figure 2, characterized by higher FRS Index values and lower FO Index values. In contrast, low job zone occupations, like pressers in textile and garment industries, cluster toward the bottom-right quadrant, exhibiting lower FRS Index values and higher FO Index values. Routine-task roles, including door-to-door sales workers, telemarketers, and procurement clerks, face elevated risks on both the FO and FRS scales, appearing around the top-right of Figure 2. This distribution results in a moderate negative correlation (r = -0.2824) between the FO and FRS indices, consistent with Hypothesis 1. Additionally, the FRS Index is negatively correlated (r = -0.5278) with the normalized scale for manual technical skill similarity levels, indicating that occupations requiring higher manual technical skills tend to have a smaller AI and LLM Displacement & Augmentation impacts.

These findings align with existing literature on the impact of automation and AI on various occupations. For instance, studies have shown that AI adoption has reduced employment in certain sectors, particularly affecting lower-skilled jobs, while high-paying occupations and those requiring advanced degrees have been less impacted (Acemoglu et al., 2020). Additionally, research indicates that automation has led to job polarization, with low-wage occupations experiencing job losses and high-wage occupations seeing gains (Autor & Dorn, 2013). These patterns underscore the complex relationship between technological advancement and labor market dynamics.

Table 1 Correlation Matrix between Different Skill Measures (obs=33,582)

	UpSkil~Z	FOprob_1	FRSn~m_1	cosine~k	norm_m~d	norm_m~w	norm_m~h	jobzon~1
UpSkill_JZ	1.0000							
FOprob_1	0.2883	1.0000						
FRSnorm_1	-0.2173	**-0.2824**	1.0000					
cosinedeta~k	0.0002	0.0232	-0.0108	1.0000				
norm_man_b~d	0.0146	0.1174	0.1497	0.1434	1.0000			
norm_man_k~w	0.0052	0.1586	0.1305	0.3798	0.2109	1.0000		
norm_man_t~h	0.0063	0.1654	**-0.5278**	0.2079	-0.1320	0.0556	1.0000	
jobzone_1	-0.5414	**-0.5439**	**0.5651**	-0.0474	0.0592	-0.0958	-0.3746	1.0000

Table 2 provides additional insights into the distribution of occupations across different Job Zones, highlighting the interplay between job preparation, skill similarity, and automation risks, shedding light on how workers in different Job Zones navigate the evolving labor market shaped by advancing technologies.

As Job Zone levels increase, the likelihood of workers facing higher risks of computerization and automation displacement (FO Index) decreases, while the probability of affected by AI-driven automation, encompassing both displacement and augmentation effects (FRS Index), increases. This opposite FO versus FRS index effect reflects Hypothesis 1.

Moreover, each occupation similarity measure—whether based on detailed task, broad tasks, domain knowledge, or technical skill similarities—reveals similar concentrations of workers across job zones. Workers' occupation similarity between years tends to decrease slightly in high Job Zones. This finding suggests that workers in jobs requiring greater preparation (associated with higher Job Zones) are less likely to remain in highly similar roles if they change jobs. This trend may reflect the higher human capital and adaptability of these workers, which could facilitate greater learning capacity and a propensity to pursue upward mobility or upgrade their roles during job transitions.

Table 2 Mean FO and FRS Indices and Different Job Skill Types by Job Zone

Job Zone	FO Index	FRS Index	Detailed Task Similarity	Broad Task Similarity	Domain Knowledge Similarity	Technical Skill Similarity
1	0.7762	0.2222	0.1670	0.6230	0.6636	0.9388
2	0.7208	0.4361	0.1679	0.5701	0.6798	0.8868
3	0.4237	0.5108	0.1724	0.5878	0.6637	0.8746
4	0.3009	0.7649	0.1547	0.6192	0.6610	0.7874
5	0.0313	0.8069	0.1364	0.5367	0.6182	0.8173

Findings based on heatmaps

Appendix Table 1 summarizes the major occupational codes and their corresponding categories to aid interpretation. Generally, the major occupational categories transition from high-skill (cognitive) to low-skill (manual) tasks, as well as cognitive tasks to routine tasks. Cognitive tasks involve mental processes such as problem-solving, critical thinking, decision-making, creativity, and information processing, whereas manual tasks involve physical effort, dexterity, or motor skills to complete specific activities.

The heatmaps show distinct patterns, indicating that occupational similarity (potential occupational mobility) varies depending on the factor being considered. For detailed tasks (Figure 1a), high-skilled cognitive occupational categories (e.g., SOC code 11–27) and low-skilled manual occupations (e.g., 47–53) show relatively high similarity, although the lower-skilled categories have a narrower range of occupations. This suggests that individuals in high-skilled cognitive tasks may have greater occupational mobility than those in lower-skilled professions—at least in terms of tasks.

In Figure 1b for the broad tasks, the lowest similarities appear in the central categories, which involve a mix of tasks associated with a broader range of skills. Also of note is that occupational mobility tends to be relatively high within certain major occupational groups, such as Education, Instruction, and Library (25) and Food Preparation and Serving Related (35), suggesting that transitioning between jobs within these sectors may be easier. When considering the importance of tasks (Figure 1b), we see a different pattern than 1b. This demonstrates the need to evaluate not only the specific tasks involved in an occupation but also their relative importance.

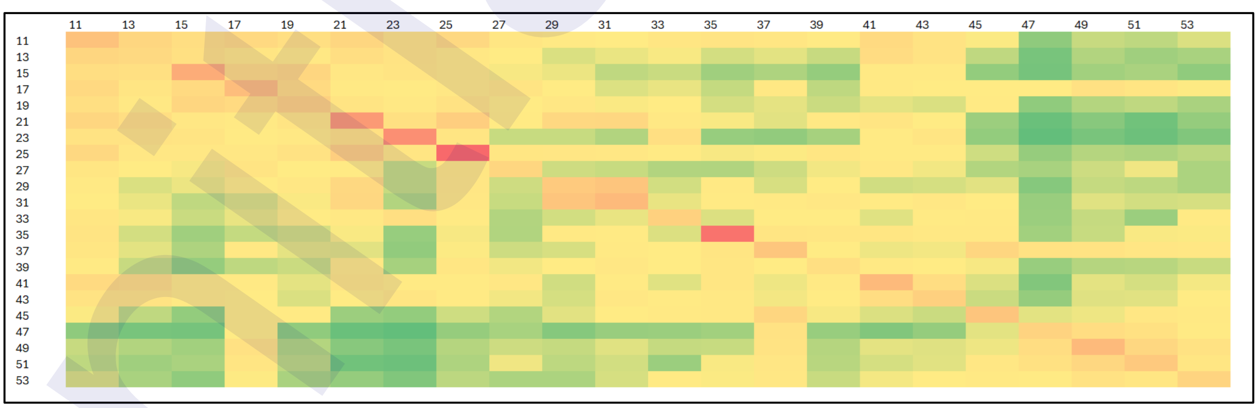
The heatmap for domain knowledge (Figure 1c) shows significant similarity within major occupational categories but significant differences across sectors. For example, fields like science exhibit distinct knowledge requirements, while areas such as production and manufacturing share more similarities.

When examining technical skills (Figure 1d), yet another pattern emerges. Variation is minimal (not fully visible on the heatmap due to the lack of normalization across minimum and maximum values), suggesting that a core set of technical skills is required across many occupations. While specialized technical skills are important in certain occupations, foundational competencies may be equally (if not, more) important for training purposes.

These findings have significant implications for understanding occupational mobility in the context of automation. As suggested, the heatmaps help identify occupations with greater mobility potential—occupations where workers might transition with minimal retraining or re-education following job displacement. However, the types and combinations of skills, expertise, and tasks needed for transitions to dissimilar occupations—whether through re-skilling, down-skilling, or up-skilling—are inherently complex.

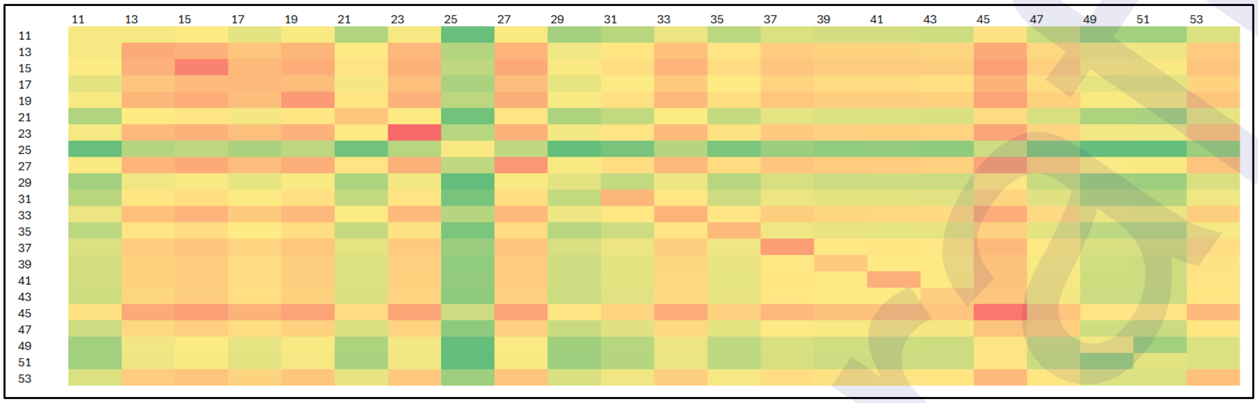
Another important consideration is the interplay between occupational similarity and automation potential. While high similarity within or between major sectors suggests easier transitions, it might also make such occupations more vulnerable to automation. For instance, a sector with substantial internal similarity could face widespread job displacement if many occupations share automatable tasks. To get to this dimension of the problem, we conduct network analysis by bringing in information on occupational automation propensities.

Figure 1a. Average Similarity Based on Detailed Tasks



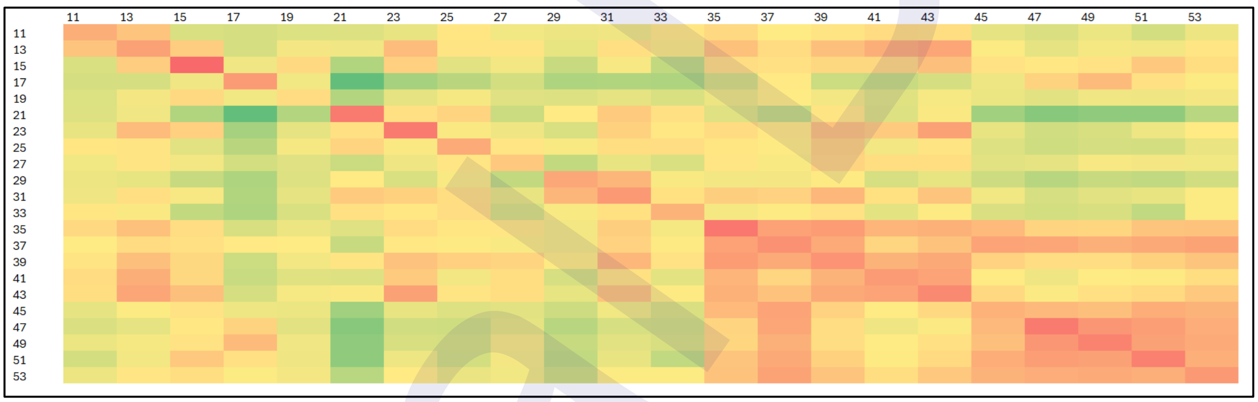
Note: Minimum=0.007579, Maximum=0.327974, Range=0.320396. Red represents higher similarity, while green indicates lower similarity.

Figure 1b. Average Similarity Based on the Importance of Broad Tasks



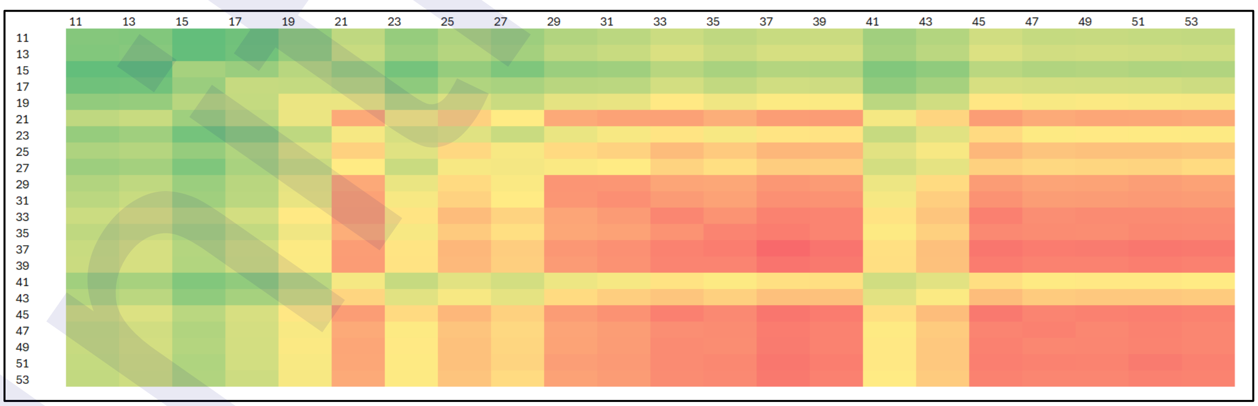
Note: Minimum: 0.38773, Maximum: 0.843489, Range: 0.455758. Red represents higher similarity, while green indicates lower similarity.

Figure 1c. Average Similarity Based on the Importance of Domain Knowledge



Note: Minimum=0.279438, Maximum=0.736821, Range=0.457383. Red represents higher similarity, while green indicates lower similarity.

Figure 1d. Average Similarity Based on the Importance of Technical Skills



Note: Minimum=0.785295, Maximum= 0.852228, Range= 0.066933. Red represents higher similarity, while green indicates lower similarity.

The heatmaps show distinct patterns, indicating that occupational similarity (potential occupational mobility) varies depending on the factor being considered. For detailed tasks (Figure 1a), high-skilled cognitive occupational categories (e.g., SOC code 11–27) and low-skilled manual occupations (e.g., 47–53) show relatively high similarity, although the lower-skilled categories have a narrower range of occupations. This suggests that individuals in high-skilled cognitive tasks may have greater occupational mobility than those in lower-skilled professions—at least in terms of tasks.

In Figure 1b for the broad tasks, the lowest similarities appear in the central categories, which involve a mix of tasks associated with a broader range of skills. Also of note is that occupational mobility tends to be relatively high within certain major occupational groups, such as Education, Instruction, and Library (25) and Food Preparation and Serving Related (35), suggesting that transitioning between jobs within these sectors may be easier. When considering the importance of tasks (Figure 1b), we see a different pattern than 1b. This demonstrates the need to evaluate not only the specific tasks involved in an occupation but also their relative importance.

The heatmap for domain knowledge (Figure 1c) shows significant similarity within major occupational categories but significant differences across sectors. For example, fields like science exhibit distinct knowledge requirements, while areas such as production and manufacturing share more similarities.

When examining technical skills (Figure 1d), yet another pattern emerges. Variation is minimal (not fully visible on the heatmap due to the lack of normalization across minimum and maximum values), suggesting that a core set of technical skills is required across many occupations. While specialized technical skills are important in certain occupations, foundational competencies may be equally (if not, more) important for training purposes.

These findings have significant implications for understanding occupational mobility in the context of automation. As suggested, the heatmaps help identify occupations with greater mobility potential—occupations where workers might transition with minimal retraining or re-education following job displacement. However, the types and combinations of skills, expertise, and tasks needed for transitions to dissimilar occupations—whether through re-skilling, down-skilling, or up-skilling—are inherently complex.

Another important consideration is the interplay between occupational similarity and automation potential. While high similarity within or between major sectors suggests easier transitions, it might also make such occupations more vulnerable to automation. For instance, a sector with substantial internal similarity could face widespread job displacement if many occupations share automatable tasks. To get to this dimension of the problem, we conduct network analysis by bringing in information on occupational automation propensities.

Findings based on Typology

Similarity between FO Index and FRS Index: Both FO index (Frey and Osborne, 2017) and FRS Index (Felten et al., 2023) measure automation risks, focusing on how automation—whether through AI, machine learning, or other technologies—affects jobs. Both measures assess which tasks within occupations are more likely to be automated, identifying routine and cognitive tasks that are susceptible to automation. Both approaches categorize occupations based on automation risks, linking automation likelihood to the type of job and its required skills.

Difference between FO Index and FRS Index: While FO Index primarily focused on *displacement* risk of jobs, assessing whether tasks in an occupation are automatable and thus likely to be replaced by machines or AI, FRS Index emphasized both *displacement* and *augmentation* risks, recognizing AI's dual role in either replacing tasks or enhancing human productivity. While FO index links to a narrower view of skill obsolescence, emphasizing jobs that become redundant due to automation, FRS Index links to a broader view that recognizes both skill obsolescence and new skill demands, considering *augmentation* alongside *displacement* and emphasizing how AI can complement human labor, leading to potential productivity gains. While FO Index concentrated on routine, repetitive, and non-cognitive tasks that are highly susceptible to automation, FRS Index addresses broader scope including non-routine cognitive tasks and tasks that AI can augment, enhancing productivity rather than fully replacing them.

Based on the FO and FRS index, we can divide the occupations into four different zones, show in Figure 2.

1. High in FRS, but Low in FO: those are the jobs that involve significant human-centric tasks and cognitive skills but low automation potential. FRS measures potential productivity boosts from AI integration, emphasizing tasks that AI can enhance.FO evaluates susceptibility to automation, which these roles resist. The examples include sociologists, management analysts, etc. We can call them AI Augmentation zone.

2. High in Both (High in FRS and FO): those are jobs that involve structured tasks and some cognitive skills but are still at risk of automation. These roles benefit from AI productivity boosts but also face significant automation risks. Examples are telemarketers, procurement clerks, door-to-door sale workers, etc. We can call them Displacement & AI Augmentation zone.

3. Low in Both (Low in FRS and FO): Jobs that involve limited AI productivity benefits and low automation risk. These are typically physical, unstructured, or creative roles resistant to AI adoption. Examples include fire fighters, janitors, etc. We can call them No Displacement No Augmentation zone.

4. Low in FRS, but High in FO: Jobs with high automation potential but minimal productivity gains from AI enhancement. These roles often consist of repetitive tasks where AI replaces humans rather than complements them. examples include pressers in textile, extractors, etc. We can call them computerized displacement zone.

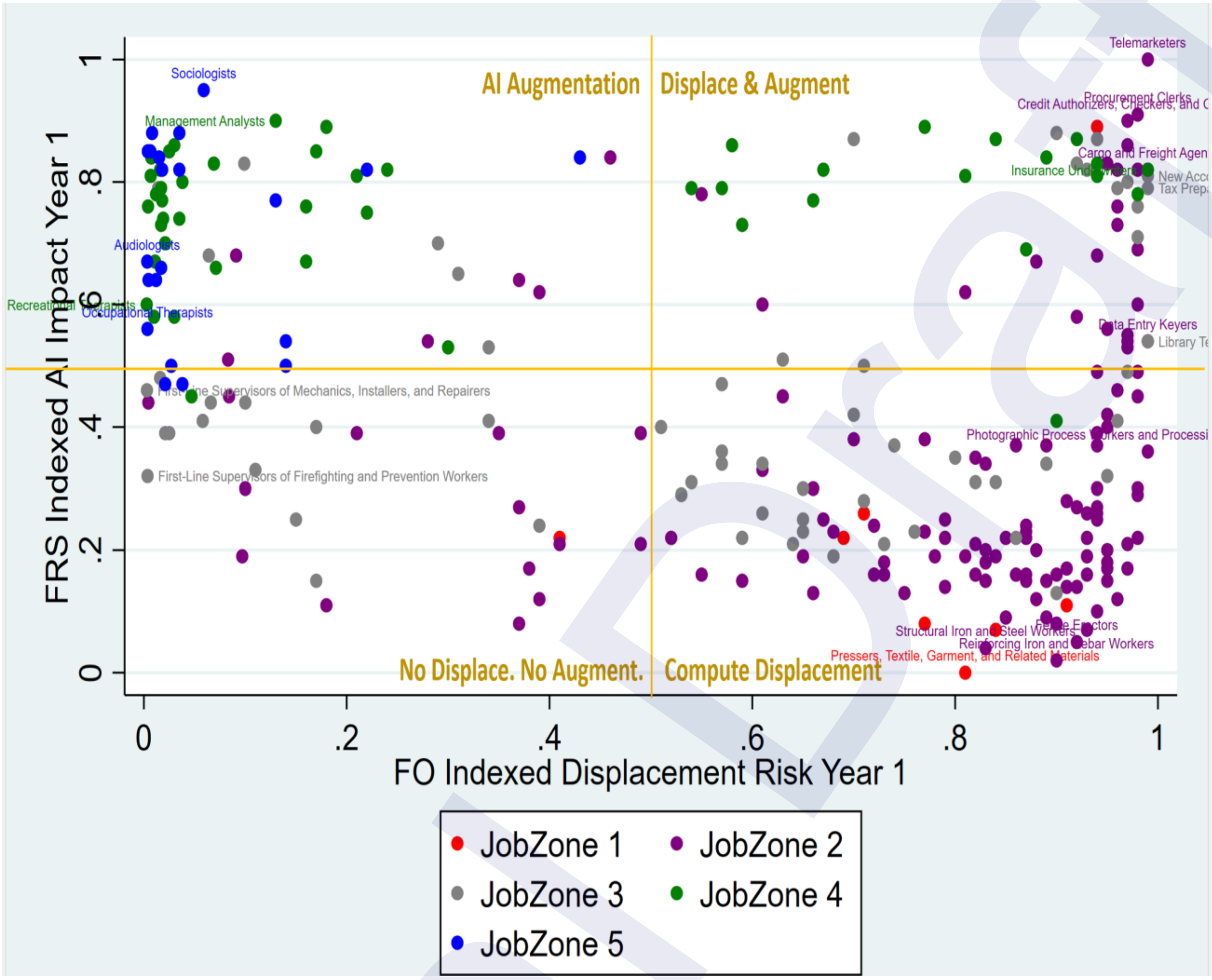
This categorization helps identify where AI complements human work versus fully automates tasks, offering insights into workforce planning and skill development. Table 3 and Figure 2 summarize this:

Table 3. The Four Occupation Types Based on FO & FRS Indices

Category	Occupation Type in Figure 2	Characteristics	Examples
High FRS, Low FO	AI Augmentation	Human-centric, cognitive roles enhanced by AI, not automated	Sociologists, management analysts, etc.
High FRS, High FO	Displacement + AI Augmentation	Structured roles at risk of automation, enhanced by AI	telemarketers, procurement clerks, door-to-door sale workers, etc
Low FRS, Low FO	No Displace No Augment	Physical/manual roles with minimal AI impact	fire fighters, janitors, etc.
Low FRS, High FO	Computer Displacement	Repetitive roles likely to be replaced, not enhanced	pressers in textile, extractors, etc.

Most high Job Zone occupations, which require greater preparation, are concentrated in the AI Augmentation Zone (Figure 2), whereas lower Job Zone occupations are predominantly found in the Computerized Displacement Zone.

Figure 2. Scatter Plot for Two Different Types of Automation Risk Scales, FO vs, FRS scales



Appendix Table 3 presents the top 10 occupations within each of the four labeled occupation types or zones, ranked using two different methods. The left side of the table lists the top 10 occupations in each type based on the number of workers, while the right-side highlights occupations with the highest or lowest FRS and FO index value combinations to represent each occupation type.

In the No Displacement No Augmentation zone, the largest occupations include chefs, first-line construction or production supervisors, packers and packagers, and electricians. In the Computerized Displacement zone, the largest occupations are laborers, carpenters, and waiters/waitresses. The Displacement and AI Augmentation zone is dominated by retail salespersons, customer service representatives, bookkeeping/accounting/auditing associates, and office clerks. Lastly, in the AI Augmentation zone, the largest occupations include first-line retail and office supervisors, chief executives, and general managers.

When considering FRS and FO indices, occupations with the lowest FRS and FO indices in the No Displacement No Augmentation zone include cleaners, mobile home installers, and upholsterers. In the Computerized Displacement zone, the lowest FRS and highest FO indices are associated with reinforcing iron and rebar workers, structural iron and steel workers, fence erectors, and industrial truck and tractor operators. The Displacement and AI Augmentation zone features the highest FRS and FO indices from telemarketers, procurement clerks, and credit authorizers/checkers/clerks. Finally, in the AI Augmentation zone, the highest FRS and lowest FO indices are found in sociologists, management analysts, public relations specialists, and clergy.

Findings from Binomial Logit Models

To address potential multicollinearity and endogeneity issues, particularly when incorporating interaction effects into the model, we utilized demeaned variable measures. This adjustment significantly reduced correlations between variables, as demonstrated in Appendix Table 2.

Table 5 presents the estimates from our binomial logit model, testing Hypotheses 1 through 3. Model (1) models the effects from each independent variable without interaction, while Model (2) interacts with the four occupation types (or zones) with year. The quadratic form of all the four similarity measures, as well as the FRS and FO indices, all catches non-linear trends.

As shown in Figure 3, the odds of upskilling display contrasting patterns when considering the FO index versus the FRS index. The odds of upskilling increase with a higher FO index but decrease with a rising FRS index, consistent with Hypothesis 1. The FO index primarily captures computerized automation effects, showing a clear rising substitution effect of labor as automation intensifies. In contrast, the FRS index reflects AI and LLM-driven automation, highlighting how increasing FRS leads to stronger impacts from both job displacement and job augmentation. The augmentation effect suggests that while workers may not face displacement, they could remain in the same job zone but experience higher productivity improvements.

Table 5. Binomial Logit Model Estimates Testing Hypotheses 1-3

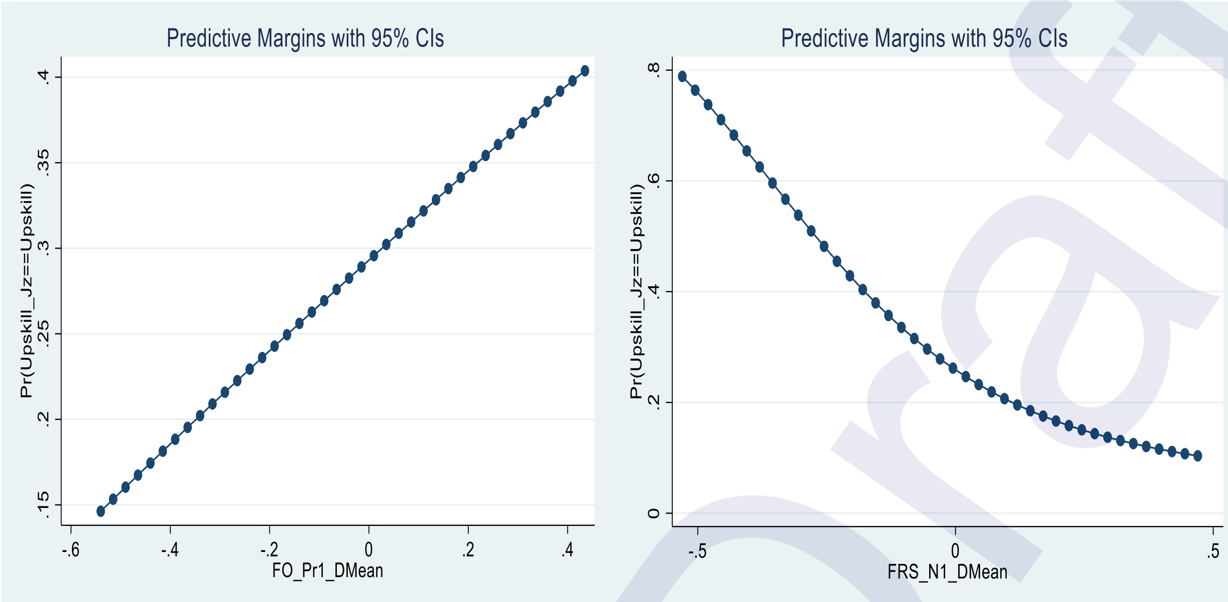
	No Interaction	Occupation Type*Yr
VARIABLES	Model (1) UpSkill	Model (2) UpSkill
2.AutomType: Computer Displacement	**-0.884***** (0.003)	-55.009*** (0.688)
3.AutomType: Displace & Augment	0.327*** (0.004)	-121.558*** (0.654)
4.AutomType: AI Augmentation	**1.938***** (0.003)	-104.563*** (0.644)
Detailed Task Similarity	3.549*** (0.005)	3.542*** (0.005)
Detailed Task Similairty^2	-11.793*** (0.022)	-11.785*** (0.022)
Broad Task Similarity	0.146*** (0.003)	0.155*** (0.003)
Broad Task Similarity^2	3.656***	3.707***

	(0.016)	(0.016)
Domain Knowledge Similarity	-1.898***	-1.891***
	(0.005)	(0.005)
Domain Knowledge Similarity^2	-1.824***	-1.818***
	(0.021)	(0.021)
Technical Skill Similarity	-5.625***	-5.638***
	(0.007)	(0.007)
Technical Skill Similarity^2	-3.762***	-3.826***
	(0.031)	(0.031)
FO Index	2.230***	2.241***
	(0.004)	(0.004)
FO Index^2	-2.460***	-2.462***
	(0.007)	(0.007)
FRS Index	-8.485***	-8.495***
	(0.005)	(0.005)
FRS Index^2	4.594***	4.629***
	(0.012)	(0.012)
Year		-0.032***
		(0.000)
2.AutomType: Computer Displacement*Year		0.027***
		(0.000)
3.AutomType: Displace & Augment*Year		0.060***
		(0.000)
4.AutomType: AI Augmentation*Year		0.053***
		(0.000)
2-Digit SOC Occupation FE	Yes	Yes
Year FE	Yes	
Location (Region) FE	Yes	Yes
Constant	-1.569***	62.504***
	(0.005)	(0.541)
Observations	33,852	33,852

Notes:

1. Standard errors in parentheses
2. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10
3. Control Variables include Age, Gender, Education Attainment, Race, Ethnicity, Marital Status, Year Immigrated, Health (Disability).
4. All similarity measures, FO and FRS indices are demeaned.

Figure 3. FO vs. FRS Indices and Upskill—H1



As expected and illustrated in Figure 4, occupations experiencing Computerized Displacement have the lowest odds of upskilling, while jobs in the AI Augmentation zone are most likely to upskill, controlling for all other factors. Compared to jobs with Low Displacement and Low Augmentation risks, those facing computerized displacement risks are 12% less likely to upskill, whereas jobs with high AI augmentation opportunities are 1.9 times more likely to upskill, holding all other variables constant. These results are presented in Table 5 and further reflects Hypothesis 2.

Figure 4. Upskill and Occupation Types—H2

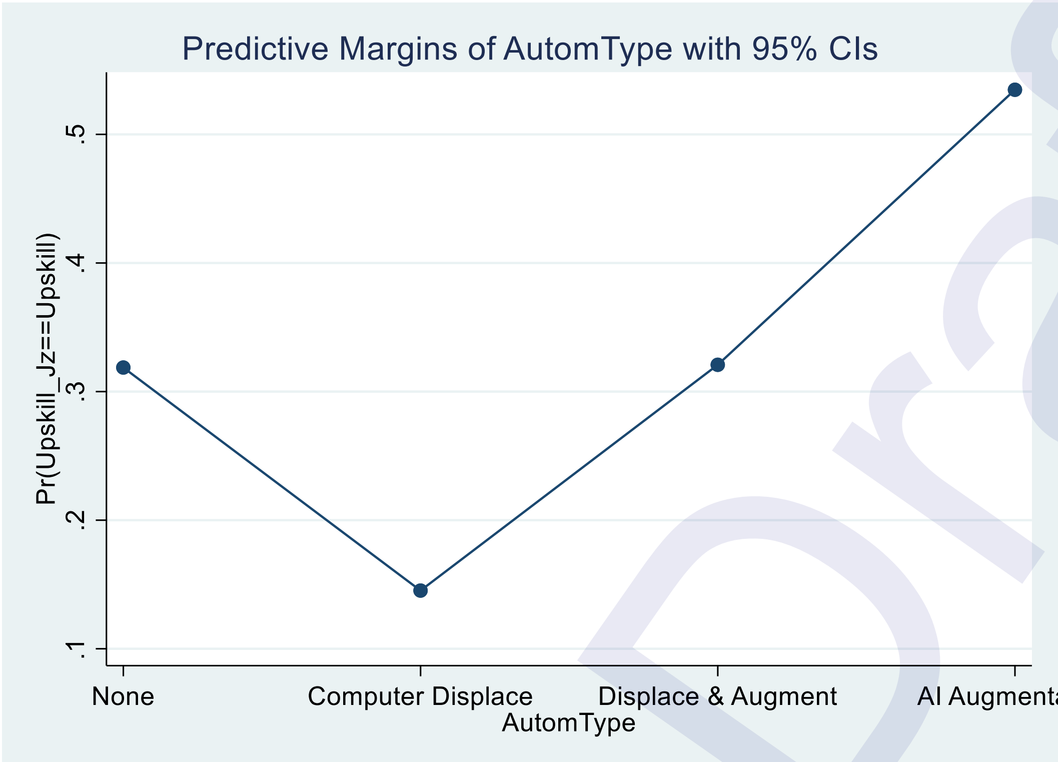
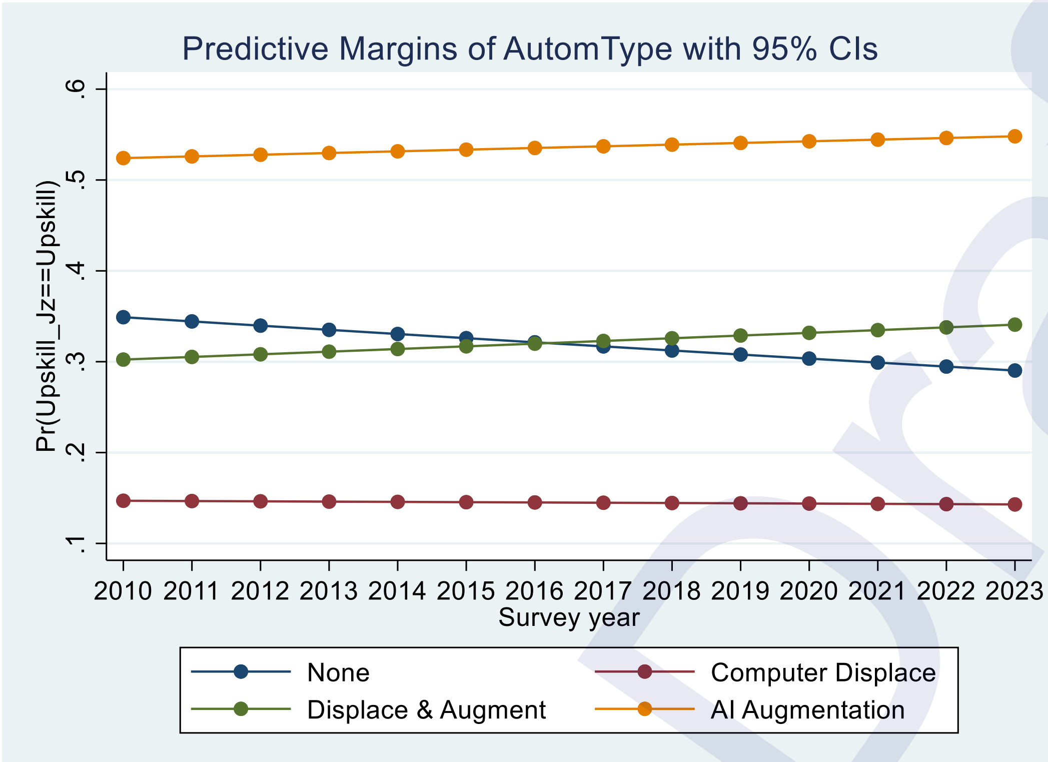


Figure 5 illustrates that while the odds of upskilling for workers facing Computerized Displacement have remained largely stable from 2010 to 2023, the odds for those facing high AI impacts—both AI Augmentation and Displacement—have consistently risen over time. Conversely, workers facing low automation risk and low AI impact have seen declining odds of upskilling, consistent with Hypothesis 3. As expected from the literature, FO and FRS capture distinct types of automation effects, and occupation similarity does not significantly enhance the odds of upskilling. Workers with low automation risk, low displacement, and low AI augmentation are less likely to experience immediate displacement, but also show declining upskilling odds over time.

Figure 5 Year, Occupation Automation Types, and Upskil—H3



As shown in Figure 6, as detailed task similarity between a worker's two jobs increases from Year 1 to Year 2, the odds of upskilling initially rise, peaking around the average similarity level before declining. This pattern is similar for technical skill similarities, though the tipping point occurs earlier. When detailed task and technical skills become highly similar, the odds of upskilling decrease. In contrast, broad task similarity initially reduces the odds of upskilling, but rises again as the similarity approaches the average level. Domain knowledge similarity, however, has a consistently negative relationship with upskilling. This is consistent with Hypothesis 4. These findings highlight that higher similarity in detailed tasks, domain knowledge, and technical skills tends to reduce upskilling, while increased similarity in broad task types can enhance upskilling odds. The detailed model estimates are presented in Table 6.

Figure 6. Upskill and Occupation Similarities—H4

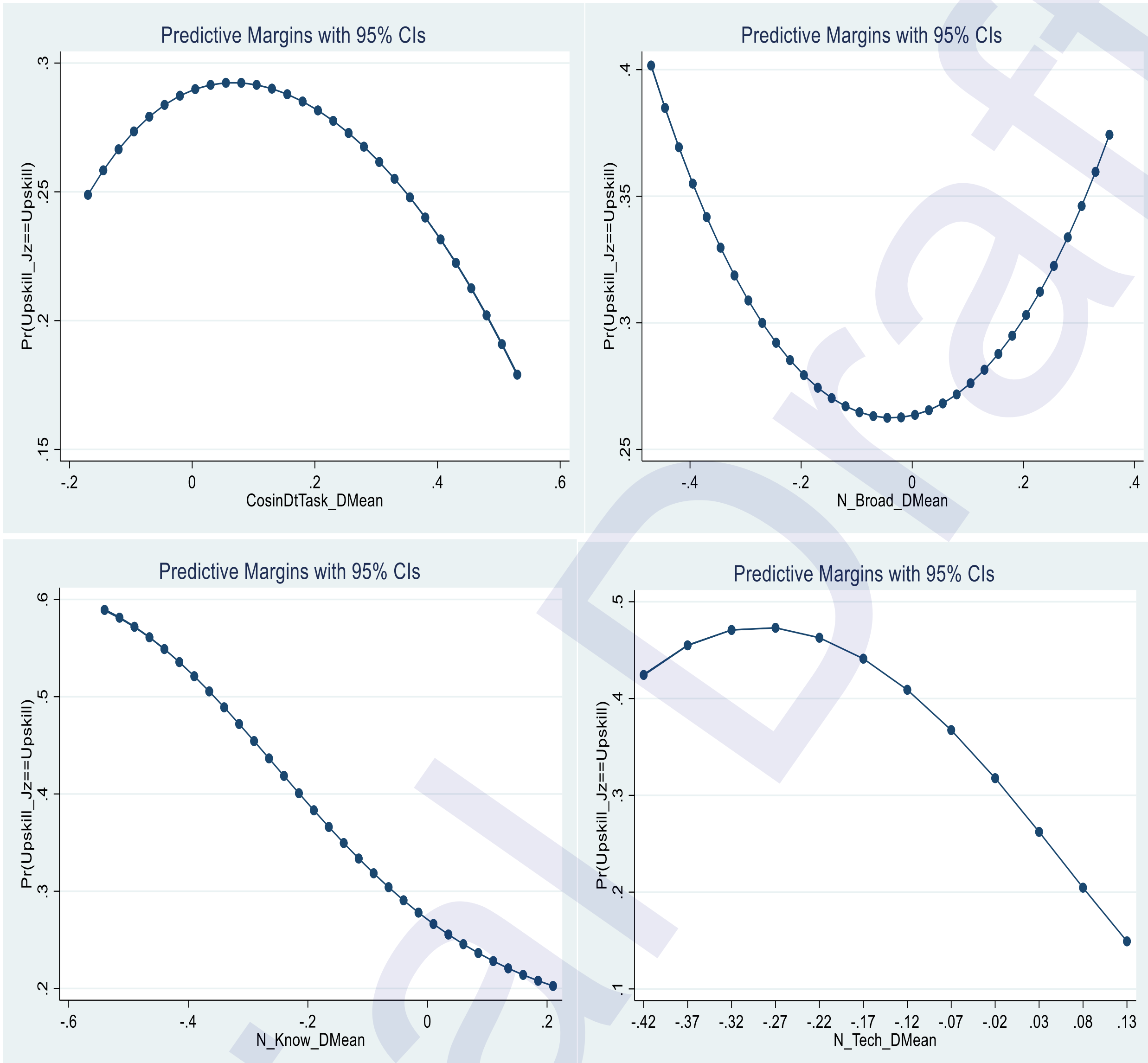


Table 6. Binomial Logit Model Estimates Testing Hypothesis 4

	Occupation Type*Detailed Task	Occupation Type*Broad Task	Occupation Type*Domain Knowledge	Occupation Type*Technical Skills
	Model (3)	Model (4)	Model (5)	Model (6)
VARIABLES	UpSkill	UpSkill	UpSkill	UpSkill
2.AutomType: Computer Displacement	-1.604***	-0.337***	-1.179***	-0.913***
	(0.004)	(0.003)	(0.003)	(0.004)
3.AutomType: Displace & Augment	-0.354***	0.672***	-0.030***	0.132***
	(0.005)	(0.004)	(0.004)	(0.005)
4.AutomType: AI Augmentation	1.830***	2.087***	1.994***	1.541***
	(0.003)	(0.003)	(0.003)	(0.003)
Detailed Task Similarity	5.687***	3.974***	3.629***	4.008***

	(0.011)	(0.005)	(0.005)	(0.005)
Detailed Task Similairty^2	-31.429***	-12.333***	-14.096***	-13.296***
	(0.066)	(0.022)	(0.022)	(0.022)
Broad Task Similarity	0.256***	-0.038***	0.400***	0.160***
	(0.003)	(0.009)	(0.003)	(0.003)
Broad Task Similarity^2	4.025***	9.696***	4.041***	3.537***
	(0.016)	(0.053)	(0.016)	(0.016)
Domain Knowledge Similarity	-1.630***	-1.963***	9.096***	-1.795***
	(0.005)	(0.005)	(0.012)	(0.005)
Domain Knowledge Similarity^2	-0.061**	-1.440***	19.049***	-1.368***
	(0.021)	(0.021)	(0.044)	(0.021)
Technical Skill Similarity	-6.165***	-5.642***	-5.680***	-11.121***
	(0.007)	(0.007)	(0.007)	(0.017)
Technical Skill Similarity^2	-5.315***	-3.265***	-4.861***	-24.006***
	(0.032)	(0.032)	(0.032)	(0.122)
FO Index	2.491***	2.021***	2.312***	2.137***
	(0.004)	(0.004)	(0.004)	(0.004)
FO Index^2	-2.708***	-2.102***	-2.804***	-2.748***
	(0.007)	(0.007)	(0.007)	(0.007)
FRS Index	-8.720***	-8.697***	-8.958***	-8.694***
	(0.005)	(0.005)	(0.005)	(0.005)
FRS Index^2	4.902***	4.141***	4.932***	4.780***
	(0.012)	(0.012)	(0.012)	(0.012)
2.AutomType: Computer Displacement*Detailed Task Similarity	-1.774***			
	(0.014)			
3.AutomType: Displace & Augment*Detailed Task Similarity	-4.685***			
	(0.014)			
4.AutomType: AI Augmentation*Detailed Task Similarity	0.261***			
	(0.014)			
2.AutomType: Computer Displacement*Detailed Task Similarity^2	26.358***			
	(0.080)			
3.AutomType: Displace & Augment*Detailed Task Similarity ^2	29.719***			
	(0.077)			
4.AutomType: AI Augmentation*Detailed Task Similarity ^2	10.176***			
	(0.078)			
2.AutomType: Computer Displacement*Broad Task Similarity		-1.410***		
		(0.010)		
3.AutomType: Displace & Augment*Broad Task Similarity		-1.748***		
		(0.011)		
4.AutomType: AI Augmentation*Broad Task Similarity		0.703***		
		(0.010)		
2.AutomType: Computer Displacement*Broad Task Similarity^2		-16.890***		
		(0.060)		
3.AutomType: Displace & Augment*Broad Task Similarity ^2		-0.848***		
		(0.063)		
4.AutomType: AI Augmentation*Broad Task Similarity ^2		-6.748***		
		(0.061)		

2.AutomType: Computer Displacement*Domain Knowledge Similarity			-12.911*** (0.015)	
3.AutomType: Displace & Augment*Domain Knowledge Similarity			-12.412*** (0.014)	
4.AutomType: AI Augmentation*Domain Knowledge Similarity			-12.868*** (0.014)	
2.AutomType: Computer Displacement*Domain Knowledge Similarity^2			-20.894*** (0.064)	
3.AutomType: Displace & Augment*Domain Knowledge Similarity ^2			-8.873*** (0.067)	
4.AutomType: AI Augmentation*Domain Knowledge Similarity ^2			-35.054*** (0.062)	
2.AutomType: Computer Displacement*Technical Skill Similarity				2.566*** (0.021)
3.AutomType: Displace & Augment*Technical Skill Similarity				10.141*** (0.021)
4.AutomType: AI Augmentation*Technical Skill Similarity				6.936*** (0.021)
2.AutomType: Computer Displacement*Technical Skill Similarity^2				5.466*** (0.158)
3.AutomType: Displace & Augment*Technical Skill Similarity ^2				31.403*** (0.131)
4.AutomType: AI Augmentation*Technical Skill Similarity ^2				29.410*** (0.134)
2-Digit SOC Occupation FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Location (Region) FE	Yes	Yes	Yes	Yes
Constant	-1.175*** (0.005)	-1.819*** (0.005)	-1.259*** (0.005)	-1.124*** (0.005)
Observations	33,852	33,852	33,852	33,852

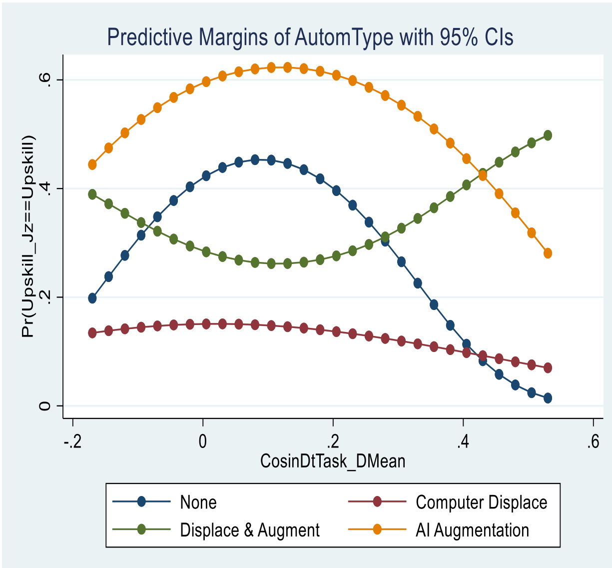
Notes:

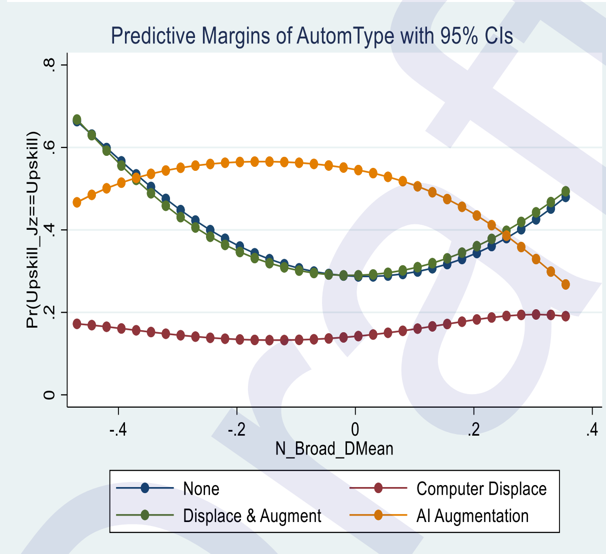
1. Standard errors in parentheses
2. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10
3. Control Variables include Age, Gender, Education Attainment, Race, Ethnicity, Marital Status, Year Immigrated, Health (Disability).
4. All similarity measures, FO and FRS indices are demeaned.

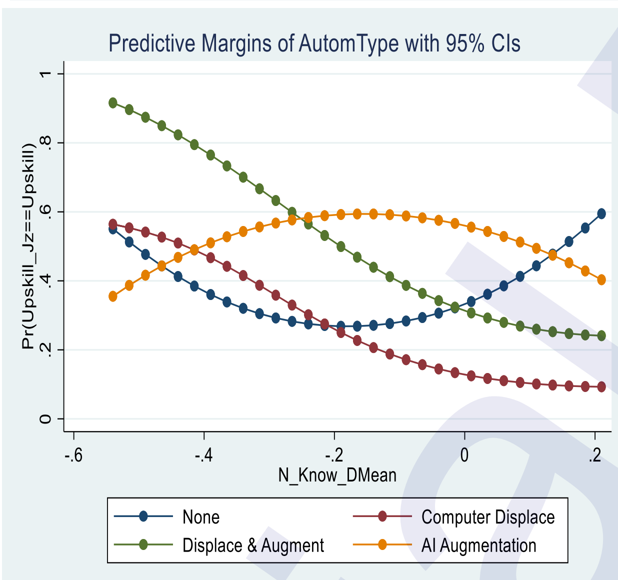
As shown in Figures 7, 4, and 5, occupations in the AI Augmentation zone are overall the most likely to upskill, while those facing high computerized displacement risks are the least likely to upskill. However, even within AI Augmentation zones, the upskill odds decline as similarities become increasingly high across detailed, broad, domain knowledge, and technical skill dimensions. For occupations experiencing both displacement and AI augmentation, upskilling odds are higher when detailed or broad task similarities increase, but decrease as domain knowledge and technical skill similarities rise. For occupations with low displacement and low augmentation risks, upskilling opportunities increase when broad and domain knowledge similarities are high, but decline as detailed task and technical skill similarities increase.

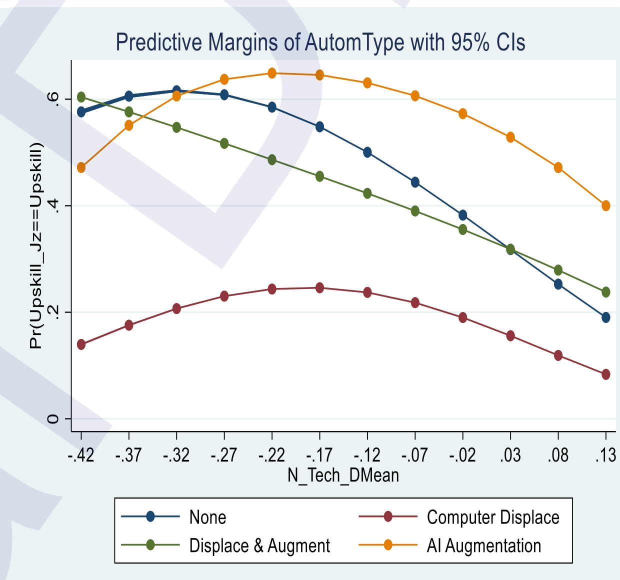
For AI Augmentation occupations, upskilling opportunities remain relatively high, but diminish when similarity levels become too high. For occupations facing both displacement and AI augmentation, the best upskilling opportunities are observed with high detailed and broad task similarities or low domain knowledge similarities. For occupations with low displacement and low augmentation risks, the best upskilling opportunities arise when broad and domain knowledge similarities are high or when technical skill similarity is low. For occupations with high computerized displacement risks, the opportunity for upskilling remains relatively limited, though broad task similarities help widen the upskilling window slightly.

Figure 7 Occupation similarity, Occupation Automation Types, and Upskil









Summary of Findings, Discussion, and Contribution

The study examines the relationship between job zones, automation risks, and AI-driven impacts on occupations. Findings reveal that high-skill, cognitively intensive jobs are less vulnerable to computerized automation but more prone to AI augmentation, while low-skill, manual jobs are more exposed to computerized automation risks. High job zone occupations, such as sociologists and management analysts, fall within the AI Augmentation zone, while low job zone roles, like textile pressers, cluster in the Computerized Displacement zone. Routine-task jobs like telemarketers show elevated risks on both FO (Computerized Automation) and FRS (AI-driven Augmentation) scales, resulting in a moderate negative correlation between FO and FRS indices. The results suggest distinct patterns of occupational distribution for four different occupation zones based on automation risk typologies, including the AI Augmentation Zone , Displacement and AI Augmentation Zone, the Computerized Displacement Zone, and No Displacement No Augmentation Zone, highlighting differing implications for upskilling and workforce planning.

The findings from this study contribute to the ongoing discourse on automation and AI's impact on labor markets. The correlation analysis between the FRS AI Displacement & Augmentation Risk Index and job zone upgrades suggests a moderate to strong positive relationship, indicating that as job zones progress, AI-driven augmentation risks (FRS Index) increase while computerized automation risks (FO Index) decrease. Specifically, high-skill, cognitively intensive occupations such as sociologists and management analysts exhibit greater AI-driven productivity gains, reflecting AI's potential for augmenting human tasks rather than fully displacing them (Felten et al., 2023). These results align with previous literature suggesting that automation tends to displace low-skill, routine-based jobs while augmenting high-skill, cognitive roles (Acemoglu & Restrepo, 2018; Autor & Dorn, 2013).

The negative correlation between FO and FRS indices ($r = -0.2824$) found in this study confirms Hypothesis 1, demonstrating a distinct divergence in the impacts of computerized automation and AI-driven augmentation. Specifically, the FO Index focuses on routine, repetitive tasks, which are more susceptible to automation, while the FRS Index accounts for both displacement and productivity gains via AI integration (Felten et al., 2023). This distinction corroborates earlier research emphasizing job polarization, where high-skill, high-wage roles are less affected by automation and may experience productivity enhancements through AI, while low-skill, low-wage jobs are more vulnerable to displacement (Autor & Dorn, 2013).

Furthermore, the relationship between the FRS Index and manual technical skill similarity highlights that occupations requiring higher manual technical skills tend to experience reduced AI-driven impacts, further emphasizing the differentiation between job types (Felten et al., 2023). The study's heatmap analysis reveals that occupations in high job zones with higher cognitive skill requirements are more likely to benefit from AI augmentation rather than being fully displaced, supporting prior research on the growing complementarity of AI with human labor in high-skill domains (Acemoglu & Restrepo, 2018).

In contrast, occupations characterized by low job zone levels, such as textile pressers, fall within the Computerized Displacement zone. These jobs face greater exposure to automation risks due to their reliance on routine, manual tasks, which are more susceptible to AI displacement (FO Index) (Frey & Osborne, 2017). This pattern is consistent with studies indicating that low-skill, repetitive occupations tend to experience significant automation-driven job losses (Autor & Dorn, 2013).

The findings related to the FO and FRS indices provide insights into how automation risks are distributed across different occupational groups or zones. While high-skill, cognitively intensive jobs benefit from AI-driven augmentation, low-skill, manual jobs are more exposed to automated displacement, further supporting the hypothesis of technological-driven job polarization (Autor & Dorn, 2013; Frey & Osborne, 2017). The study also highlights that while job zone similarity between years tends to decrease for high-skill jobs, such workers are more likely to engage in occupational mobility through upskilling or re-skilling (Felten et al., 2023).

Overall, the current findings offer a nuanced understanding of how automation and AI affect different occupational groups, contributing to the ongoing dialogue on the future of work, job displacement, and skill development (Acemoglu & Restrepo, 2018).

This study makes several unique contributions compared to prior literature. First, it differentiates between computerized automation risks (FO Index) and AI-driven augmentation risks (FRS Index), providing a more nuanced understanding of how automation impacts vary across occupations. While previous studies, such as Frey and Osborne (2017) and Acemoglu & Restrepo (2018), primarily focused on job polarization due to routine, low-skill tasks being automated, this study goes beyond by emphasizing AI's role in enhancing productivity in high-skill cognitive jobs, rather than just focusing on displacement. The finding that AI augmentation tends to complement human labor in these high-skill roles, while computerized automation predominantly affects low-skill, routine jobs, highlights the complex and multifaceted nature of automation impacts.

Second, the introduction of a four-occupation zone framework—AI Augmentation, Computerized Displacement, Displacement & Augmentation, and No Displacement No Augmentation zones—provides a clearer typology of how AI and automation risks are distributed across occupations. Prior research often categorized jobs into binary categories (e.g., high vs. low displacement), but this study's detailed classification offers more precise insights into how different types of jobs experience varying levels of AI and automation impacts. By categorizing jobs based on their automation risk profiles, the study contributes a more comprehensive understanding of the distinct dynamics at play in different sectors.

Third, the study's exploration of occupation similarity and upskilling dynamics presents a significant contribution to the existing literature. Previous research has examined the relationship between skill mismatch and automation, but this study goes further by analyzing how occupational similarity affects upskilling behaviors. It finds that higher technical and domain knowledge similarity decreases upskilling opportunities, while broad task similarity increases them. These nuanced findings challenge earlier studies that treated skill similarity as a straightforward concept, providing a more refined understanding of how occupational similarity influences labor market adaptability.

Fourth, this study's longitudinal approach, spanning over a decade from 2010 to 2023, offers critical insights into how automation risks and upskilling trends evolve over time. While much of the existing literature provides cross-sectional snapshots of automation impacts, this study's temporal analysis reveals that jobs with high AI augmentation risks are increasingly likely to experience upward mobility, whereas jobs facing computerized displacement risks are less likely to upskill. This temporal dimension enriches the understanding of how automation risks and occupational mobility interact in the long term.

Lastly, the use of heatmap and network analysis methodologies represents a methodological contribution that has not been fully emphasized in previous studies. By mapping task and skill similarity patterns across different job zones, the study provides new insights into the complex relationship between occupational similarity and automation risks. This approach allows for a deeper understanding of how these risks are distributed within and between occupational sectors, offering a novel perspective on the role of task similarity in predicting automation impacts.

In summary, this study contributes to prior literature by refining and extending key concepts such as automation risk, AI augmentation, and occupational mobility. Its novel framework, nuanced analyses, and methodological advancements offer a more detailed and comprehensive understanding of how automation risks are distributed across job zones, providing valuable insights for workforce development and policy-making strategies.

3. Conclusion and Implications

This study offers significant contributions to the existing body of research on automation, AI, and labor market dynamics. By distinguishing between AI-driven augmentation and computerized automation, the study provides a more nuanced framework for understanding how automation impacts different job zones. The categorization of occupations into AI Augmentation, Computerized Displacement, Displacement & Augmentation, and No Displacement No Augmentation zones allows for a more detailed analysis of how automation risks are distributed across the workforce. The findings highlight the complex relationship between occupational similarity, AI-driven changes, and upskilling opportunities, contributing to a deeper understanding of the forces shaping labor market outcomes. Furthermore, the study's emphasis on the role of AI in productivity enhancement versus job displacement expands upon existing research, particularly by emphasizing the dynamic interplay between AI and human capital development.

The findings of this study carry important implications for policymakers, educators, and workforce planners. First, the differentiation between AI augmentation and computerized displacement provides a critical lens for identifying strategies to mitigate automation risks while fostering upskilling opportunities in AI-driven roles. For occupations within the AI Augmentation zone, targeted interventions such as training programs, reskilling initiatives, and education focused on enhancing cognitive and technical skills can support workers in maintaining productivity gains and upward mobility. For occupations in the Computerized Displacement zone, efforts should prioritize retraining in roles less susceptible to automation, particularly through the development of broader, transferable skills.

Additionally, the findings emphasize the importance of investing in human capital and promoting lifelong learning to ensure that workers in high-skill, cognitively intensive roles can adapt to evolving labor market demands. These findings suggest that industries dependent on routine and low-skill tasks may face greater automation risks, highlighting the need for targeted policies aimed at fostering job creation and growth in high-skill, high-value areas.

Policymakers should focus on promoting sector-specific interventions that support automation resilience, particularly by encouraging diversification in industries and sectors with lower automation risk. The study also calls for increased support in education and training systems that can enhance the adaptability of workers and reduce the prevalence of job polarization. Developing strategies that enable workers to transition smoothly across job zones—particularly those involving greater AI augmentation—can foster resilience in the face of automation.

Finally, these results underscore the necessity of integrating AI-driven labor market forecasts into workforce planning efforts to ensure alignment between education, training, and labor market needs. By understanding the nuanced impacts of automation, policymakers can better design interventions that enhance workforce productivity, reduce the mismatch between skills and job demands, and ensure a more equitable labor market.

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Appendix

Table 1. Major Occupational Codes and Categories

Code	Category
11	Management
13	Business and Financial Operations
15	Computer and Mathematical
17	Architecture and Engineering
19	Life, Physical, and Social Science
21	Community and Social Service
23	Legal
25	Education Instruction and Library
27	Arts, Design, Entertainment, Sports, and Media
29	Healthcare Practitioners and Technical Occupations
31	Healthcare Support
33	Protective Services
35	Food Preparation and Serving Related
37	Building and Grounds Cleaning and Maintenance
39	Personal Care and Service
41	Sales and Related
43	Office and Administrative Support
45	Farming, Fishing, and Forestry
47	Construction and Extraction
48	Installation, Maintenance, and Repair
51	Production
53	Transportation and Material Moving
55	Military Specific

Note: We exclude category 55 from the analysis.

Table 2 Correlation matrix of modeling variables (obs=33,852)

```
             | UpSkil~Z AutomT~e CosinD~n N_Broa~n N_Know~n N_Tech~n FO_Pr1~n
FRS_N1~n    age_1    sex_1    EDU_1    EDU_2 Hispan~1 Marita~1 Marita~2
yrimmi~1   Race_1 diffan~1 diffan~2

-------------+---------------------------------------------------------------
------------------------------------------------------------------------------
-----------------------------

  UpSkill_JZ |   1.0000

   AutomType |  -0.0793   1.0000

CosinDtTas~n |   0.0002   0.0039   1.0000
```

```
N_Broad_DM~n |   0.0146   0.0203   0.1434   1.0000

N_Know_DMean |   0.0052   0.0867   0.3798   0.2109   1.0000

N_Tech_DMean |   0.0063  -0.4405   0.2079  -0.1320   0.0556   1.0000

FO_Pr1_DMean |   0.2883  -0.3033   0.0232   0.1174   0.1586   0.1654   1.0000

FRS_N1_DMean |  -0.2173   0.7003  -0.0108   0.1497   0.1305  -0.5278  -0.2824
1.0000

       age_1 |  -0.0252   0.1157   0.0280   0.0316   0.0101  -0.0915  -0.1025
0.1203   1.0000

       sex_1 |   0.0030   0.1148   0.0286   0.0874   0.1541  -0.1035   0.1201
0.2694   0.0065   1.0000

       EDU_1 |  -0.0085   0.3398  -0.0206   0.0872   0.0030  -0.3407  -0.1985
0.3902   0.0716   0.0196   1.0000

       EDU_2 |   0.0084   0.3285  -0.0216   0.0896   0.0042  -0.3413  -0.1871
0.3794   0.0507   0.0229   0.8994   1.0000

  Hispanic_1 |   0.0024  -0.1240   0.0100  -0.0375  -0.0160   0.1321   0.0757
-0.1553  -0.1386  -0.0244  -0.1752  -0.1809   1.0000

MaritalSta~1 |   0.0202  -0.1231  -0.0082  -0.0192  -0.0032   0.1015   0.1398
-0.1177  -0.4534   0.0328  -0.0981  -0.0839   0.0641   1.0000

MaritalSta~2 |   0.0178  -0.1198  -0.0066  -0.0188  -0.0019   0.0998   0.1400
-0.1162  -0.4365   0.0325  -0.1013  -0.0882   0.0664   0.9449   1.0000

   yrimmig_1 |  -0.0083  -0.0943   0.0449  -0.0254  -0.0300   0.0898   0.0259
-0.1283   0.0059  -0.0216  -0.0638  -0.0733   0.4387  -0.0658  -0.0624
1.0000

      Race_1 |  -0.0025  -0.0210   0.0140   0.0040   0.0006   0.0175   0.0261
-0.0139  -0.0510   0.0290   0.0168   0.0148  -0.0684   0.0691   0.0725
0.2174   1.0000

   diffany_1 |  -0.0040  -0.0073   0.0095   0.0018   0.0030   0.0191   0.0105
-0.0195   0.1114  -0.0134  -0.0251  -0.0249  -0.0335   0.0045   0.0083  -
0.0349  -0.0012   1.0000

   diffany_2 |   0.0005  -0.0164   0.0012   0.0005   0.0004   0.0205   0.0086
-0.0202   0.1099  -0.0086  -0.0257  -0.0281  -0.0296   0.0122   0.0153  -
0.0307  -0.0070   0.3312   1.0000
```

Table 3. Top 10 Occupations by Counts and FRS-FO Index Values in Each Occupation Type

Ranking Method	Top 10 Largest Occupation by Occupation Type				Rank	Top 10 Highest/Lowest FRS-FO Index by Occupation Type				
Occupation Type	Occupation	Freq.	%	Cum		FRS	FO	Job Zone	SOC2018	SOC2018 Title

No Displace No Augment	Chefs and Head Cooks	1,118	24	24	1	0.08	0.37	2	29-1081	Cleaners of Vehicles and Equipment
No Displace No Augment	First-Line Supervisors of Constructio..	627	14	38	2	0.11	0.18	2	21-2011	Manufactured Building and Mobile Home Installers
No Displace No Augment	First-Line Supervisors of Production ..	476	10	48	3	0.12	0.39	2	29-1031	Upholsterers
No Displace No Augment	Packers and Packagers, Hand	372	8	56	4	0.15	0.17	3	17-2141	Firefighters
No Displace No Augment	Electricians	294	6	62	5	0.17	0.38	2	41-9031	Packers and Packagers, Hand
No Displace No Augment	Childcare Workers	291	6	69	6	0.19	0.10	2	51-1011	Electrical Power-Line Installers and Repairers
No Displace No Augment	Farmers, Ranchers, and Other Agricult..	245	5	74	7	0.21	0.41	2	29-1122	Structural Metal Fabricators and Fitters
No Displace No Augment	First-Line Supervisors of Mechanics, ..	238	5	79	8	0.21	0.49	2	49-1011	Telecommunications Line Installers and Repairers
No Displace No Augment	Cleaners of Vehicles and Equipment	170	4	83	9	0.22	0.41	1	29-1181	Graders and Sorters, Agricultural Products
No Displace No Augment	Hairdressers, Hairstylists, and Cosme..	109	2	85	10	0.24	0.39	3	33-1021	Elevator and Escalator Installers and Repairers
Computer Displace	Laborers and Freight, Stock, and Mate..	1,072	9	9	1	0.02	0.90	2	29-2081	Reinforcing Iron and Rebar Workers
Computer Displacet	Construction Laborers	1,047	9	18	2	0.04	0.83	2	39-2021	Structural Iron and Steel Workers
Computer Displace	Carpenters	766	6	24	3	0.05	0.92	2	37-2021	Fence Erectors
Computer Displace	Waiters and Waitresses	726	6	30	4	0.07	0.93	2	51-4041	Industrial Truck and Tractor Operators
Computer Displace	Food Preparation Workers	632	5	35	5	0.07	0.84	1	51-6021	Plasterers and Stucco Masons
Computer Displace	Inspectors, Testers, Sorters, Sampler..	446	4	39	6	0.08	0.90	2	49-2091	Roofers
Computer Displace	Shipping, Receiving, and Inventory Cl..	402	3	43	7	0.08	0.77	1	35-3041	Dishwashers
Computer Displace	First-Line Supervisors of Food Prepar..	394	3	46	8	0.09	0.89	2	49-3031	Rail-Track Laying and Maintenance Equipment Operators
Computer Displace	Maids and Housekeeping Cleaners	365	3	49	9	0.09	0.85	2	51-2011	Laborers and Freight, Stock, and Material Movers, Hand
Computer Displace	Automotive Service Technicians and Me..	353	3	52	10	0.10	0.94	2	35-1012	Tire Builders
Displace & Augment	Retail Salespersons	1,442	14	14	1	1.00	0.99	2	29-1011	Telemarketers
Displace & Augment	Customer Service Representatives	1,373	13	27	2	0.91	0.98	2	29-1131	Procurement Clerks
Displace & Augment	Bookkeeping, Accounting, and Auditing..	841	8	35	3	0.90	0.97	2	2601198	Credit Authorizers, Checkers, and Clerks
Displace & Augment	Office Clerks, General	790	8	43	4	0.89	0.94	1	29-1041	Door-to-Door Sales Workers, News & Street Vendors, Related Workers

Displace & Augment	Receptionists and Information Clerks	745	7	50	5	0.89	0.77	4	19-4021	Purchasing Agents, Except Wholesale, Retail, & Farm Products
Displace & Augment	Accountants and Auditors	680	7	56	6	0.88	0.90	3	15-2011	Human Resources Assistants, Except Payroll & Timekeeping
Displace & Augment	Insurance Sales Agents	293	3	59	7	0.87	0.94	3	47-2111	Interviewers, Except Eligibility and Loan
Displace & Augment	Property, Real Estate, and Community ..	276	3	62	8	0.87	0.92	4	13-2061	Insurance Sales Agents
Displace & Augment	Personal Financial Advisors	275	3	65	9	0.87	0.84	4	13-1011	Proofreaders and Copy Markers
Displace & Augment	Billing and Posting Clerks	257	2	67	10	0.87	0.70	3	33-3021	Eligibility Interviewers, Government Programs
AI Augment	First-Line Supervisors of Retail Sale..	2,217	21	21	1	0.95	0.06	5	43-2011	Sociologists
AI Augment	First-Line Supervisors of Office and ..	981	9	30	2	0.90	0.13	4	47-2073	Management Analysts
AI Augment	Chief Executives	868	8	38	3	0.89	0.18	4	13-2031	Public Relations Specialists
AI Augment	General and Operations Managers	793	7	45	4	0.88	0.01	5	41-2022	Clergy
AI Augment	Construction Managers	733	7	52	5	0.88	0.04	5	43-3021	Lawyers
AI Augment	Food Service Managers	708	7	58	6	0.86	0.03	4	51-7042	Purchasing Managers
AI Augment	Financial Managers	657	6	65	7	0.85	0.00	5	43-4141	Dietitians and Nutritionists
AI Augment	Management Analysts	458	4	69	8	0.85	0.01	5	25-4031	Speech-Language Pathologists
AI Augment	Medical and Health Services Managers	335	3	72	9	0.85	0.03	4	43-3051	Directors, Religious Activities and Education
AI Augment	Computer & Information Systems Mana..	241	2	74	10	0.85	0.17	4	49-9091	Financial Examiners