

Artificial Intelligence Exposure, Tacit Experience and Occupational Wage Growth

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Abstract

Artificial-intelligence exposure measures where new technologies could affect work, but they do not reveal how exposure translates into labour-market outcomes. I combine the AI Occupational Exposure Index with U.S. state–occupation wage growth from 2018 to 2024 and construct indices of codified knowledge and tacit experience from O*NET. Across 26,697 cells and 662 occupations, a one-standard-deviation increase in tacit experience is associated with a 0.015-log-point steeper exposure–wage-growth gradient ($SE = 0.003$), conditional on codified knowledge, initial wages and state fixed effects. The pattern survives broader controls, occupation-level aggregation, item resampling and a 2023–2024 window; the corresponding codified-knowledge result is less stable. Employer reports independently link tacit experience to prior experience and on-the-job training. These occupational associations do not identify effects of actual adoption. They show that employment outcomes depend on how work organises and values experience-based judgement.

Keywords: artificial intelligence; occupational knowledge; tacit experience; technological change; work organisation; wage growth

1. Introduction

Measures of artificial intelligence exposure now organise much of the debate about the future of work. They identify occupations whose tasks or abilities overlap with new technical capabilities,

but they do not show whether employers adopt those capabilities, how work is redesigned, or how gains and losses are distributed. Industrial-relations research instead treats digitalisation as an organisational and institutional process. Workplace evidence shows that sectoral arrangements and worker representation shape the implementation of robotics and its job outcomes (Lloyd and Payne, 2021), while recent occupation-level evidence links automation risk to worker health (Vasiakina and Dudel, 2026). This article brings that perspective to U.S. occupational wage change.

The empirical puzzle is straightforward. Occupations with similar measured exposure to large language models do not necessarily follow the same wage path. Exposure indices are intentionally technology-centred: they map capabilities to occupational content. Jobs, however, are also social and institutional bundles. They combine formal knowledge, practised judgement, credentials, autonomy, responsibility and bargaining positions. These features affect whether a new tool standardises work, extends managerial control, complements workers, or changes which contributions employers reward. An occupation-level account of technological change should therefore ask not only where AI can reach, but also what kind of knowledge remains situated in workers and how that knowledge is organised.

I study this question through the distinction between codified knowledge and tacit experience. Codified knowledge can be stated, documented and transmitted through rules, texts, formal instruction and credentials. Tacit experience is learned through practice and expressed in judgement, anticipation of error, negotiation and decisions under uncertainty. The distinction is not a division between automatable and protected jobs. Most professional and technical occupations require both. It instead identifies two ways that occupational capability is produced and made valuable. Digital systems can make codified material easier to reproduce, while

simultaneously increasing the importance of workers who interpret outputs, manage exceptions or remain accountable for consequential decisions. Conversely, employers may also use technology to capture and centralise workers' situated knowledge. The direction of change is therefore an empirical question rather than a property of the technology alone.

To examine this occupational mediation, I construct a Codified Knowledge Index (CKI) and a Tacit Experience Index (TEI) from O*NET and merge them with the Felten-Raj-Seamans AI Occupational Exposure Index (AIOE) and Occupational Employment and Wage Statistics for 2018-2024. CKI combines knowledge domains, basic skills, certification and apprenticeship requirements. TEI measures experience-based skills and work contexts involving judgement, error anticipation, negotiation, autonomy and responsibility. The matched sample contains 26,697 state-occupation cells from 51 jurisdictions and 662 occupations. Because AIOE, CKI and TEI vary at the occupation level, the independent variation comes from those occupations rather than from every state-occupation cell.

The central result concerns tacit experience. A one-standard-deviation increase in TEI is associated with a 0.015-log-point steeper AIOE wage-growth gradient ($SE = 0.003$), conditional on CKI, initial wages and state fixed effects. The association remains positive with broader controls, unweighted occupation aggregation, leave-one-state-out estimation, O*NET-item resampling and in the 2023-2024 window. Employment weighting reduces its magnitude, showing that the pattern is clearer for the average occupation than for the employment-weighted average worker. CKI has a negative baseline interaction of -0.008 ($SE = 0.003$), but it is more sensitive to controls and index construction. Independent Occupational Requirements Survey measures provide a content check: CKI aligns with formal education, while TEI aligns with prior experience and on-the-job training.

The article makes three contributions. First, it qualifies exposure-based accounts of artificial intelligence and work. Existing measures locate potential technological reach (Felten, Raj, and Seamans, 2021; Webb, 2019; Eloundou et al., 2024), but they do not specify how work is reorganised or whose knowledge is rewarded. The analysis shows that occupational knowledge composition separates wage trajectories within levels of exposure. Second, it extends task-based research by distinguishing codified content from judgement acquired through practice. Research on technological change documents both task reallocation and shifts in skill requirements (Autor, Levy, and Murnane, 2003; Gekara and Nguyen, 2018; Consoli et al., 2023). CKI and TEI identify a dimension that a single routine/non-routine classification does not fully capture when language models can perform some non-routine cognitive tasks. Third, the article adds occupation-level wage evidence to industrial-relations research showing that the consequences of digitalisation depend on institutions, workplace actors and the organisation of knowledge. It identifies experience-based judgement as one margin along which labour-market outcomes differ among similarly exposed occupations.

This interpretation also distinguishes the article from direct studies of AI use. Experiments and workplace deployments show that generative AI can improve performance, often unevenly across workers and tasks (Noy and Zhang, 2023; Brynjolfsson, Li, and Raymond, 2025; Dell'Acqua et al., 2026). The present data do not observe adoption, use intensity or worker-level outcomes. They instead reveal an occupation-level pattern in the period surrounding rapid diffusion of language models. The analysis is consequently framed as evidence about the social and occupational differentiation of potential exposure, not as an estimate of technology's causal effect on wages.

The remainder of the article develops this argument in four steps. The next section explains why codification and tacit experience provide a useful account of occupational mediation. The following sections describe the data, indices and empirical strategy, before presenting the wage patterns and robustness checks. The discussion returns to what the findings imply for the organisation and valuation of knowledge under technological change.

2. Technological Change and the Organisation of Occupational Knowledge

2.1. From Technical Exposure to Occupational Outcomes

Exposure indices answer an important but limited question: where do the capabilities of a technology overlap with occupational content? They do not show whether employers adopt the technology, which tasks are delegated, how output is monitored, or whether productivity gains accrue to workers. These outcomes depend on choices about work organisation and on institutions that distribute discretion, responsibility and bargaining power. The distinction matters especially for large language models because they operate across text, code and communication rather than within a narrow set of routine operations. Their technical reach may be broad even where their organisational use remains partial or contested.

This article therefore treats the AIOE measure as potential exposure and the estimated interactions as conditional occupational associations. The approach does not assume that AI arrives as an external shock with uniform effects. It asks whether wage change during a period of expanding AI capability varies systematically with pre-existing occupational knowledge arrangements. This is a form of occupational mediation: the relationship between technical

exposure and an observed labour-market outcome differs according to how occupations produce and organise expertise.

The routine/non-routine distinction provides a natural benchmark. Earlier computerisation disproportionately affected work that could be represented by explicit rules, while non-routine analytical and interpersonal tasks were comparatively harder to automate (Autor, Levy, and Murnane, 2003). Language models blur this boundary because they can generate text and code, summarise information and assist with tasks commonly classified as non-routine cognitive work. Routine intensity may consequently understate variation within contemporary professional and technical occupations. Evidence from workplaces likewise shows that digitalisation can transform both job roles and the mix of technical, generic and interpersonal skills that workers use (Gekara and Nguyen, 2018). A more specific account of how knowledge is articulated and acquired is needed.

2.2. Codification, Experience and the Organisation of Expertise

Polanyi's distinction between explicit and tacit knowledge supplies that account. Codified knowledge can be recorded and transmitted through texts, rules, procedures, formal instruction and credentials. Codification lowers the cost of communicating knowledge, but it does not make context or judgement irrelevant (Polanyi, 1966; Cowan, David, and Foray, 2000). In occupations, codification also has an institutional form. Educational requirements, certification and occupational standards establish who is authorized to perform work and how competence is recognized. The Codified Knowledge Index captures both substantive knowledge domains and these formalised requirements.

Generative AI is closely connected to codification because its training material and interfaces are built around text, code, images and other recorded representations. This creates a plausible route through which exposed codified activities can be reproduced or reorganised. Yet a negative interaction between AIOE and CKI would not mean that formal knowledge has become unnecessary. Codified expertise may remain essential for defining problems, verifying outputs and maintaining professional authority. Credentials can also sustain occupational rents. The empirical coefficient therefore captures a conditional wage-growth pattern, not a direct measure of substitution.

Tacit experience refers to capability acquired through practice that is difficult to fully articulate in advance. It appears in recognising unusual cases, anticipating consequences, negotiating with others, balancing competing objectives and accepting responsibility for decisions. The Tacit Experience Index operationalises these features through O*NET skills and work contexts. Such experience can complement AI when workers must interpret model output or manage exceptions. It can also become a target of managerial extraction: digital systems may formalise workers' situated knowledge and relocate control. Research on algorithmic management shows precisely this tension between participation and the centralisation of knowledge (Krzywdzinski, Schneiss, and Sperling, 2025). A positive TEI interaction should thus be read as evidence that experience-based capability is associated with a more favourable occupational wage trajectory, not as proof that workers are technologically protected or empowered.

Codified and tacit knowledge are not mutually exclusive. Medicine, law, engineering and many skilled trades combine formal education with supervised practice. Their wages may also reflect licensing, organisational hierarchy and bargaining institutions. This overlap is why the empirical analysis enters CKI and TEI jointly and conditions on initial wages. Initial wage

summarises a broad bundle of training, credentials, experience, authority and rents. It predicts exposure-related wage change, but it does not identify which part of the bundle matters. CKI and TEI separate two observable components while leaving other institutional sources of occupational advantage explicit as limitations.

This paper’s framework yields two conditional expectations. First, if exposure more readily reorganises work centred on recorded knowledge, the AIOE-wage-growth gradient should be less favourable in occupations with higher CKI, holding TEI and initial wages constant. Second, if practised judgement remains valuable in the organisation of exposed work, the gradient should be more favourable in occupations with higher TEI, holding CKI and initial wages constant. In coefficient terms, the expected signs are $\beta(\text{AIOE} \times \text{CKI}) < 0$ and $\beta(\text{AIOE} \times \text{TEI}) > 0$. These signs describe differentiation within exposure; they do not identify the effect of adoption.

A final analysis is deliberately exploratory. Cognitive requirements may strengthen the TEI gradient if judgement is especially valuable in cognitively demanding occupations. They may instead absorb part of TEI if both indices capture occupational complexity. The triple interaction among AIOE, TEI and cognitive requirements is therefore treated as a boundary test rather than as a central hypothesis.

3. Research Design and Measurement

3.1. Data Sources

I combine BLS Occupational Employment and Wage Statistics (OEWS) for 2018–2024, O*NET 28.3, and the Felten-Raj-Seamans AIOE measure. The outcome is the 2018–2024 change in log mean annual wages, winsorized at the 1st and 99th percentiles. The matched data contain

26,697 state-occupation cells and 662 occupations. The 2024 cross section has 27,462 cells, and the RCI comparison has 25,898. Because OEWS reports cell means rather than worker panels, measured wage changes may include shifts in worker, establishment, or industry composition. A data audit found 331 duplicate year-state-SOC records, all in the 2019 District of Columbia file. The annual-window code collapses each duplicate set to one cell.

AIOE is an exposure score. It does not record adoption, intensity of use, or realized automation. Every state cell in an occupation receives the same AIOE, CKI, and TEI values. In statistical terms, the exposure variation comes from 662 occupations, not 26,697 separate treatments.

O*NET supplies the inputs for CKI, TEI, and Cog. AIOE is also mapped from O*NET abilities. Although the item sets differ, common occupational complexity, rating error, or SOC crosswalks could correlate the measures. The National Center for O*NET Development (2024) documents the release.

3.2. Index Construction

I construct CKI, TEI, and Cog from O*NET items selected before estimation. The three measures vary at the occupation level, and I standardise their underlying items across occupations.

CKI contains 33 Knowledge items, 10 Basic Skills items, and Importance ratings for Job-Related Professional Certification and Job-related Apprenticeship. Supporting Information Table S10 removes each source group in turn. The negative CKI gradient disappears when Knowledge items are removed but survives the removal of Basic Skills or certification and apprenticeship.

TEI averages 25 experience-dependent Skills items and 11 Work Context items. Supporting Information Table S10 shows a positive gradient for both components, 0.013 ($p < 0.001$) for the skills-only index and 0.004 ($p = 0.048$) for the context-only index. The comparison does not isolate experience from authority or responsibility.

Cog aggregates 20 O*NET cognitive-ability Importance items, including Deductive Reasoning, Inductive Reasoning, Mathematical Reasoning, Oral Comprehension, and Written Comprehension. It covers all occupations in the SOC sample.

I standardise each element within its O*NET source file before combining sources. This step puts IM items (rated 1–5) and CX items (which use different ranges) on a common scale. Each index is the unweighted mean of its elements within an occupation and is then standardised across occupations.

3.3. Descriptive Statistics

Table 1 describes the matched data. CKI correlates 0.624 with TEI and 0.781 with Cog. AIOE has a stronger correlation with Cog (0.665) than with CKI (0.513), and only a weak correlation with TEI (0.099).

The indices overlap without measuring the same thing. Centred-variable VIFs stay below 2.64. I read the joint coefficients as conditional associations among related occupation measures, not effects of independent constructs.

Table 1: Descriptive Statistics and Pairwise Correlations

Panel A.		Descriptive statistics					
Variable	Mean	SD	P10	P25	P50	P75	P90
wage (2018)	10.854	0.476	10.275	10.500	10.812	11.171	11.479
wage (2024)	11.050	0.416	10.551	10.739	11.003	11.327	11.617
wage growth	0.210	0.132	0.052	0.135	0.212	0.288	0.365
AIOE (z)	0.000	1.000	-1.267	-0.871	-0.016	1.005	1.297
CKI (z)	-0.021	0.989	-1.314	-0.761	-0.022	0.694	1.247
TEI (z)	-0.025	1.011	-1.356	-0.712	0.010	0.685	1.324
Cog (z)	-0.034	0.998	-1.356	-0.749	0.009	0.724	1.272
Panel B.		Pairwise correlations among standardized indices					
AIOE	1.000	0.513	0.099	0.665			
CKI	0.513	1.000	0.624	0.781			
TEI	0.099	0.624	1.000	0.656			
Cog	0.665	0.781	0.656	1.000			

Notes: Unit of observation is a state-6-digit SOC occupation. Wage variables used to construct $\Delta \ln(\text{wage})$ are observed in 2018 and 2024; $\Delta \ln(\text{wage})$ is winsorized at the 1st and 99th percentiles. Panel B reports Pearson correlations among standardised AIOE, CKI, TEI, and Cog.

3.4. Analytical Strategy

I estimate interaction models of the form:

$$\Delta \ln \text{wage}_{js} = \beta_1 \text{AIOE}_j + \beta_2 \text{CKI}_j + \beta_3 \text{TEI}_j + \beta_4 (\text{AIOE}_j \times \text{CKI}_j) + \beta_5 (\text{AIOE}_j \times \text{TEI}_j) + \gamma \ln \text{wage}_{js,2018} + \delta (\text{AIOE}_j \times \ln \text{wage}_{js,2018}) + \mu_s + \varepsilon_{js} \quad (9)$$

Occupation j and state s index the regression cells. Although the sample contains 26,697 observations, AIOE, CKI, and TEI vary across only 662 occupations. I cluster standard errors by state and occupation and also estimate models on occupation-level aggregates.

For the exploratory cognitive extension, I add cognitive requirements and their lower-order and triple interactions to the baseline model:

$$\begin{aligned}
\Delta \ln wage_{js} = & \beta_1 AIOE_j + \beta_2 CKI_j + \beta_3 TEI_j + \beta_4 (AIOE_j \times CKI_j) + \beta_5 (AIOE_j \times TEI_j) \\
& + \gamma \ln wage_{js,2018} + \delta (AIOE_j \times \ln wage_{js,2018}) \\
& + \beta_6 Cog_j + \beta_7 (AIOE_j \times Cog_j) + \beta_8 (TEI_j \times Cog_j) \\
& + \beta_9 (AIOE_j \times TEI_j \times Cog_j) + \mu_s + \varepsilon_{js}
\end{aligned}$$

(10)

The triple interaction is an exploratory boundary test rather than a causal parameter.

The main checks change what receives weight and where the sampling uncertainty enters. I estimate at the cell and occupation levels, use alternative employment weights, resample occupations and O*NET items, and shorten the wage window to 2022–2024 or 2023–2024. I also compare element-equal and PCA indices on the same complete-case sample and remove the CKI and TEI source components one at a time.

4. Results

4.1. AI Exposure and Occupational Wage Structure

AIOE is positively associated with occupational wages in the 2024 cross section. Table S1 presents cross-sectional regressions of log occupational wages on the AIOE index for 2024, using the full sample of 27,462 state-occupation observations.

The 2024 cross section shows a steep exposure-wage gradient. A one-standard-deviation increase in AIOE predicts 0.211 log points higher annual wages (about 23.5%) after state fixed effects. SOC major-group fixed effects reduce the coefficient by 4.5%. Employment weighting raises it slightly; winsorizing wages or dropping Washington, D.C., changes little. Thus, high-

exposure occupations already occupied a different part of the wage distribution before the wage-growth regressions.

This cross-sectional fact is background, not the outcome of interest. I next compare routine intensity and initial wage as moderators of wage growth, then replace the broad wage measure with CKI and TEI.

4.2. Why Exposure Alone Is Insufficient

I first compare two moderators of the AIOE wage-growth gradient. Routine cognitive intensity represents the established task-based benchmark; initial wage captures a broader occupational bundle of training, credentials, experience, authority and rents. These comparisons show how much heterogeneity is left for the more specific CKI and TEI measures to explain.

I estimate separate and joint moderator specifications:

$$\Delta \ln wage_{js} = \beta_1 AIOE_j + \lambda RCI_j + \beta_2 (AIOE_j \times RCI_j) + \beta_3 (AIOE_j \times \ln wage_{js,2018}) + \gamma \ln wage_{js,2018} + \mu_s + \varepsilon_{js} \quad (11)$$

Table S2 compares the two moderators.

Initial wage is the stronger benchmark. The routine interaction is 0.003 (SE = 0.002), and the initial-wage interaction is 0.029 (SE = 0.006). When both enter, AIOE x RCI remains small while AIOE x initial wage is nearly unchanged. The comparison is descriptive: wage level bundles multiple occupational advantages and does not identify a mechanism.

Table S3 reports AIOE wage-growth gradients at selected percentiles of the 2018 wage distribution, computed from the joint model. Reporting them in percentage points makes the interaction easier to interpret.

The AIOE gradient is negative near the bottom of the initial-wage distribution and positive near the top. At the 10th percentile, a one-standard-deviation rise in AIOE predicts 2.5 percentage points slower wage growth. At the 90th percentile, it predicts 1.4 points faster growth. This spread motivates the effort to unpack the attributes contained in initial wage.

Table S4 compares the incremental explanatory contribution of the two moderators using partial R-squared.

The difference in incremental fit is large. The initial-wage interaction adds 0.762% to R-squared, versus 0.016% for RCI, a ratio of about 47.5 to 1. Initial wage is therefore more informative about heterogeneity in the exposure-wage-growth gradient, but it is less interpretable. CKI and TEI are introduced next to separate two knowledge-related components of this broad occupational bundle.

4.3. Knowledge Composition and Wage Change

Table 2 presents the core specifications on a constant sample of 26,697 cells.

Table 2: AIOE Interaction with CKI and TEI

	(1) CKI only	(2) TEI only	(3) Joint
AIOE	−0.392*** (0.077)	−0.297*** (0.080)	−0.319*** (0.077)
CKI	0.010*** (0.003)		−0.007** (0.003)
AIOE × CKI	−0.003 (0.002)		−0.008** (0.003)
TEI		0.028*** (0.003)	0.031*** (0.003)
AIOE × TEI		0.011*** (0.002)	0.015*** (0.003)
lnwage	−0.138*** (0.008)	−0.174*** (0.009)	−0.171*** (0.009)
AIOE × lnwage	0.036*** (0.007)	0.028*** (0.007)	0.030*** (0.007)
Observations	26,697	26,697	26,697
R-squared	0.208	0.228	0.231

Notes: Two-way state×occupation clustered standard errors in parentheses. All models include state fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. CKI = Codified Knowledge Index; TEI = Tacit Experience Index. AIOE and all O*NET-derived indices are z-scored.

Table 2 contains the main estimate. AIOE × TEI is 0.015 in the joint model (SE = 0.003, $p < 0.001$), compared with 0.011 when TEI enters alone. AIOE × CKI is −0.008 (SE = 0.003, $p = 0.012$), compared with −0.003 in the CKI-only regression. Both interactions grow in absolute value when estimated together. The pattern is consistent with suppression: correlated occupation attributes have conditional associations of opposite sign.

The CKI main effect moves from 0.010 in the CKI-only model to −0.007 in the joint model. Because the indices and interactions are correlated, the joint coefficient compares occupations at

mean AIOE and TEI. The sign change reflects that different comparison; it is not evidence of substitution.

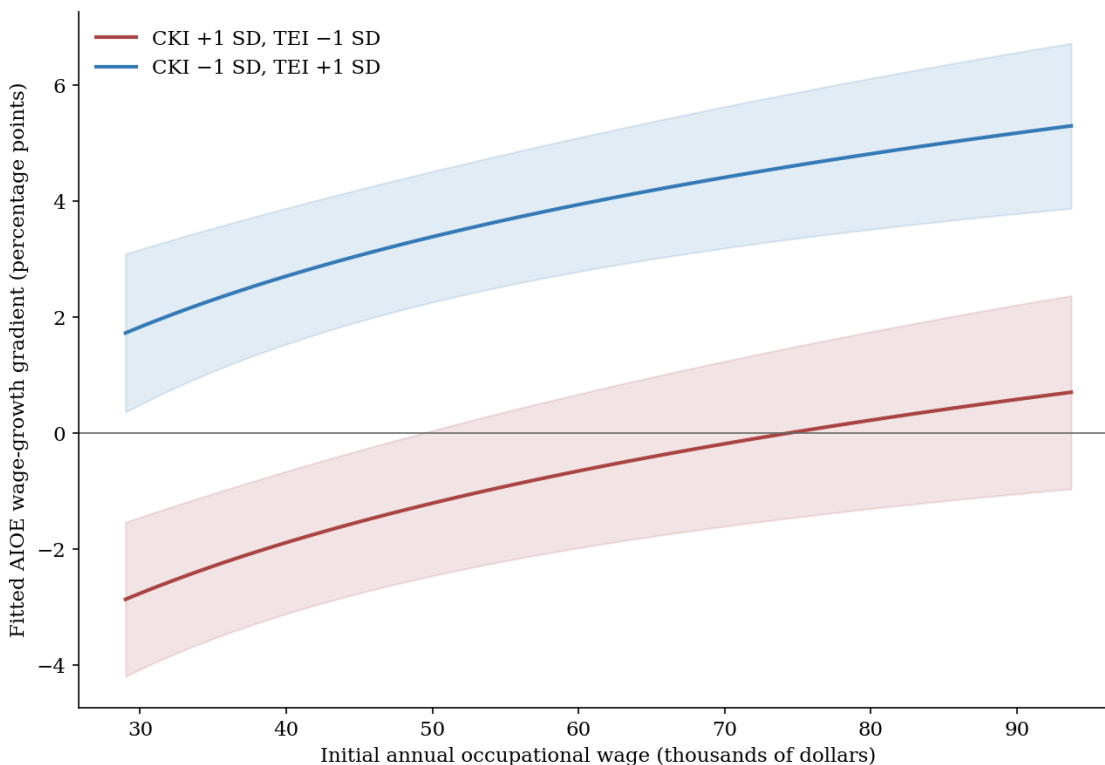


Figure 1: Estimated AIOE Wage-Growth Gradient by Knowledge Composition

Figure 1 traces the estimated AIOE wage-growth gradient for two occupation profiles. The codified-dominant profile sets CKI to +1 SD and TEI to -1 SD; the tacit-dominant profile does the reverse. The first gradient is negative over most of the wage distribution, whereas the second is positive. Their distance changes with initial wage because the model includes $\text{AIOE} \times \text{initial wage}$.

4.4. Relative Explanatory Contribution

TEI also contributes more incremental fit. It adds 0.00581 to R-squared, versus 0.00133 for CKI, a ratio of 4.38. The corresponding F-statistics are 28.51 and 6.80, with p-values below 0.001 and 0.012. This is an in-sample comparison, not a structural decomposition. It nevertheless matches the coefficient evidence that TEI is the more informative moderator.

4.5. Cognitive Requirements as an Exploratory Boundary

Table S5 presents the cognitive-moderation estimates. Column (1) uses a two-way interaction model; column (2) adds the triple interaction.

The cognitive extension does not support the exploratory expectation. Evaluated at -1, 0 and +1 SD of Cog, the cross-partial rises from 0.001 to 0.007, but all three confidence intervals include zero (Supporting Information Table S6). The triple interaction is positive and imprecise ($p = 0.112$). Adding Cog and its lower-order terms also reduces AIOE x TEI from 0.015 to 0.004, an attenuation of about 74%. TEI may contain a cognitive component, or both indices may partly measure occupational complexity. This specification cannot separate the two explanations.

5. Robustness and External Validation

The first set of checks changes the estimand. Table 3 compares state-occupation cells with occupation-level regressions. Column (1) uses the cells; columns (2) and (3) collapse the data to one observation per occupation, first without weights and then with 2018 employment weights. Removing cells with missing or nonpositive 2018 employment before aggregation leaves the same 661 occupations in both regressions.

Table 3: Main Estimands by Unit and Employment Weighting

	(1) State-occ.	(2) Occupation	(3) Occupation WLS
AIOE $\times$ CKI	−0.008** (0.003)	−0.013*** (0.003)	−0.015** (0.006)
AIOE $\times$ TEI	0.015*** (0.003)	0.015*** (0.003)	0.007 (0.006)
Observations	26,697	661	661
R-squared	0.231	0.392	0.644

Notes: Column (1) uses state-occupation cells and two-way clustered standard errors. Columns (2) and (3) report HC3 standard errors after aggregation to occupations. Before aggregation, cells with missing or nonpositive 2018 employment are removed; the resulting common sample contains 661 occupations. Column (3) weights by total 2018 occupational employment.

Aggregation preserves both signs; employment weighting changes the magnitude. The TEI coefficient falls from 0.015 in the unweighted occupation model to 0.007, while AIOE $\times$ CKI is −0.015. TEI describes the average occupation more clearly than the employment-weighted average worker. CKI remains negative and TEI positive in all 51 leave-one-state-out runs. These runs exclude domination by a single state, but not occupation-level confounding.

In 2023–2024, the window closest to widespread public use of language models, TEI is 0.004 and CKI is −0.002. Supporting Information Table S11 reports these wage estimates together with the employment-growth diagnostic.

Table S7 presents two resampling exercises, one over occupations and one over O*NET items.

Occupation and item resampling answer different questions. Resampling occupations keeps both baseline confidence intervals away from zero. Under item resampling, TEI remains positive [0.0089, 0.0216], while the CKI interval includes zero [−0.0116, 0.0004]. Supporting Information Table S9 fixes the sample at 17,359 cells: element-equal indices remain significant, whereas PCA

indices do not. The PCA result therefore reflects index construction, not sample loss alone. Supporting Information Table S10 traces CKI to the Knowledge block; both TEI blocks retain positive gradients.

Table S8 asks whether CKI and TEI add information beyond routine intensity. It includes all three interactions on a common sample.

In the simultaneous specification, $AIOE \times RCI$ is positive and statistically significant (0.006, $SE = 0.003$), but adds little to fit. On the common sample, incremental R-squared is 0.00039 for CKI, 0.00364 for TEI, and 0.00016 for RCI. TEI's increment is about 9.3 times CKI's and 22.8 times RCI's. These are in-sample predictive comparisons. The positive RCI coefficient does not amount to a rejection of the Autor-Levy-Murnane framework.

I next examine inference and observed confounding. Clustering only by state overstates precision. For CKI, state, occupation, and two-way standard errors are 0.002, 0.003, and 0.003; the corresponding values for TEI are identical. The preferred two-way p-values are 0.012 for CKI and below 0.001 for TEI. With SOC major-group fixed effects, CKI is -0.002 and TEI 0.010. The full-control estimates are -0.003 and 0.012.

The checks produce a clear ranking. TEI stays positive with cell controls, in 2023–2024, after component deletion, across leave-one-state-out runs, and under item resampling. Employment weighting and the PCA complete-case model reduce its precision. CKI is more sensitive to fixed effects, weights, index design, and the later window. The evidence for the TEI gradient is stronger.

The BLS Occupational Requirements Survey (ORS) provides an external content check. ORS asks establishments about job requirements and is independent of O*NET. CKI correlates 0.728 with minimum formal education (employment-weighted $r = 0.738$); TEI correlates 0.642 with prior

experience and on-the-job training (weighted $r = 0.724$). When both O*NET indices enter the same regression, CKI predicts education and TEI predicts prior experience and OJT (Supporting Information Table S12).

ORS validates index content more clearly than it reproduces the wage gradient. On the same 12,239 cells, the O*NET TEI interaction is 0.010. The core ORS replacement is 0.006 (SE = 0.004, $p = 0.141$), with a 95% confidence interval of -0.002 to 0.014 . The broader ORS measure is 0.010 in its 13,677-cell sample and 0.003 on the fixed sample. These replacement estimates appear in Supporting Information Table S13. Supporting Information Table S14 reports joint tests: the original and external TEI interactions are jointly significant ($p = 0.005$), whereas the CKI pair and the authority, licensing and management interactions are not. I use ORS to assess measurement, not as a second estimate of the TEI wage gradient.

Once CKI and TEI enter, RCI has little independent predictive content. Its interaction is positive and statistically significant, but its partial R-squared is only 0.00016. That is limited explanatory power, not a substantive reversal of the task-based framework.

6. Discussion

The findings show why technical exposure alone is an incomplete account of labour-market change. Among occupations with similar AIOE and initial wages, those that rely more on tacit experience have a more favourable wage-growth gradient. The TEI interaction is positive in the state-occupation and unweighted occupation models, in the 2023-2024 window, after removing either source component and under O*NET-item resampling. CKI is negative in the baseline joint model but less stable across controls, weights and index construction. The asymmetry matters: the

evidence is stronger for differentiation by experience-based judgement than for a general devaluation of codified knowledge.

The pattern connects occupational wage evidence to industrial-relations research on the social shaping of technology. Lloyd and Payne (2021) show at workplace level that sectoral and national institutions influence the pace and job consequences of digitalisation. Vasiakina and Dudel (2026) show that occupational automation risk is associated with worker health. This article studies a different outcome and unit of observation, but reaches a compatible point: an exposure score is not an employment relationship. It identifies experience-based judgement as one occupational feature associated with how wage trajectories separate during a period of expanding artificial intelligence capability. The evidence cannot show whether the association reflects productivity complementarity, occupational authority, licensing, bargaining power or changes in workforce composition.

The distinction also refines the routine/non-routine framework. Routine intensity adds little explanatory power once initial wage enters, whereas TEI separates occupations inside broad cognitive and professional categories. This does not make task-based theory obsolete. It shows that the dimensions relevant to one technological period need not be sufficient for another. Language models operate on some non-routine cognitive material, making the relation between documented knowledge and situated judgement especially important. Workplace research reaches a compatible conclusion from a different level of analysis: digital systems are implemented through negotiations over data, knowledge and control rather than simply inserted into a fixed production process (Schaupp, 2023; Krzywdzinski, Schneiss, and Sperling, 2025).

The ORS comparison helps interpret the indices without resolving the causal mechanism. Employer reports link CKI to minimum formal education and TEI to prior experience and on-the-

job training. This cross-source alignment indicates that the two O*NET indices capture recognizable dimensions of occupational requirements. The ORS replacement interactions are less precise, however, and do not reproduce the TEI gradient as clearly. The validation evidence is therefore about measurement content, not an independent confirmation of the wage relationship.

The employment-weighted result further limits the interpretation. TEI is 0.015 in the unweighted occupation model but 0.007 and imprecise when occupations are weighted by employment. Tacit experience differentiates the average occupation more clearly than the employment-weighted average worker. The analysis should not be translated into a claim that most workers in high-TEI occupations received an AI-related wage premium. OEWS reports cell means, so observed changes can reflect shifts in workers, establishments or industries as well as changes in the price of labour.

Nor should TEI be treated as a list of occupations protected from automation. A positive wage gradient says nothing directly about work intensity, surveillance, autonomy or the distribution of productivity gains within workplaces. Employers may reward experienced judgement, rely on it without increasing worker control, or attempt to encode and centralise it. Research at the firm and worker levels is needed to distinguish these possibilities. Linking adoption dates to task allocation, supervisory practices and worker outcomes would show whether TEI operates through productivity complementarity, occupational authority, licensing, rent capture or workforce composition.

These limits also define the practical implication. Policy and organisational responses should not infer workforce vulnerability from exposure scores alone. Formal training is important, but occupations also reproduce capability through supervised practice, discretion and responsibility. Whether AI strengthens or weakens those arrangements depends on how systems are implemented

and who controls the knowledge generated in use. The present evidence identifies tacit experience as a consequential dimension for that inquiry; it does not prescribe a universal strategy of reskilling or technology adoption.

7. Conclusion

Occupational exposure to generative AI does not determine a single wage trajectory. In U.S. state-occupation data for 2018-2024, the exposure-wage-growth gradient is more favourable where work relies more heavily on tacit experience. The baseline AIOE x TEI coefficient is 0.015 and remains positive across broader controls, unweighted occupation aggregation, item resampling and the 2023-2024 period. The corresponding CKI interaction is negative in the baseline model but less robust.

The contribution is not a new forecast of which occupations will survive AI. It is an account of why exposure must be interpreted through the organisation of occupational knowledge. Codified expertise, practised judgement, credentials, responsibility and bargaining positions coexist inside jobs. TEI isolates one experience-based component that broad wage levels and routine-task measures otherwise combine.

Because the data measure potential exposure rather than adoption, the analysis stops short of attributing wage change to AI. Its value lies in identifying the occupational margin that direct studies of implementation should examine. Future work can ask not only whether organisations adopt language models, but whether adoption preserves, redistributes or captures the situated judgement on which exposed work depends.

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Declaration of Generative AI and AI-Assisted Technologies

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Conflict of Interest

The author reports no potential conflicts of interest.

Data Availability

The source data are publicly available from the U.S. Bureau of Labor Statistics Occupational Employment and Wage Statistics and Occupational Requirements Survey, the National Center for O*NET Development, and the AIOE source cited in the article. The processed files and code needed to reproduce the reported results are available from the corresponding author for peer review and will be deposited in a public repository upon acceptance.

Ethics Statement

The study uses public, aggregate occupational data and does not involve human participants or identifiable personal data; ethics approval and informed consent were therefore not required.

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