

# Still Waiting for the Shock: AI's Limited Impact on Early-Career Vacancies, Skills and Tasks

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**Abstract**—This analysis of 620,000 UK apprenticeship vacancies suggests that AI is not the primary cause of declining opportunities, which instead stems from structural labour market weaknesses. The research utilized DistilRoBERTa to map digital skills from unstructured text and Google Gemini 1.5 Flash to dynamically generate an occupation-specific task taxonomy. Econometric results show no significant impact on overall vacancy volumes or technical task density. However, a modest increase in digital skill requirements was found for higher-level roles, suggesting AI complements advanced qualifications rather than displacing them. While intermediate roles have collapsed, findings attribute this to policy shifts like the Apprenticeship Levy rather than automation.

**Index Terms**—Apprenticeships, digital skills, artificial intelligence

## I. INTRODUCTION

OVER the past seven years, the United Kingdom youth labour market has experienced profound structural volatility, exacerbated by the scarring effects of the COVID-19 pandemic, the cost-of-living crisis, and the rapid integration of generative artificial intelligence. As of early 2026, approximately 957,000 young people aged 16 to 24 are classified as not in education, employment, or training, driving the youth unemployment rate to 16.0 percent (Office for National Statistics, 2026). Concurrently, the apprenticeship system has undergone a radical transformation, systematically squeezing out the traditional youth entry-level market.

Moving beyond speculative discourse, this study utilizes a novel dataset of 619,629 government apprenticeship vacancies to empirically track the evolution of entry-level job roles before and after artificial intelligence integration. The methodology integrates advanced natural language processing and large language model techniques to map occupations to the European Skills, Competences, Qualifications and Occupations framework. This allows for a granular analysis of task composition and the identification of digital skill intensity within specific roles.

The empirical analysis is structured around three central hypotheses designed to capture different dimensions of arti-

ficial intelligence induced labor disruption. The first hypothesis posits that the disruption caused by artificial intelligence impacts the total volume of job adverts, specifically measured by a reduced growth rate of vacancies in apprenticeship standards requiring extensive digital skills. The null hypothesis posits no such macroeconomic impact on vacancy volumes. The second hypothesis evaluates skill composition, suggesting that artificial intelligence disruption increases the digital skills expected in roles, with this shift expected to be more significant for higher apprenticeships. The null hypothesis posits no impact on skill composition. The third hypothesis examines task shifts, suggesting that artificial intelligence leads to task reductions or significant shifts within standards defined by extensive digital skills. The null hypothesis asserts no significant change in the task composition of these roles.

By employing a rigorous difference-in-differences design with placebo tests, the research ensures the observed trends are statistically robust, providing a precise technical evaluation of how artificial intelligence is reshaping the demand for early-career skills. Preliminary findings indicate that the null hypotheses for overall vacancy volumes and technical task shifts cannot be rejected. However, digital skill requirements have measurably increased for higher-level educational roles.

## II. LITERATURE REVIEW AND POLICY BACKGROUND

### A. The Youth Labour Market and Apprenticeships

Historically, entry-level roles served as a vital training ground where young workers performed routine cognitive tasks to acquire domain expertise. Following the introduction of the Apprenticeship Levy in 2017, the volume of apprenticeship starts contracted sharply, stabilizing at volumes approximately 30 percent below their pre-Levy peaks (Department for Education, 2026). The defining trend within this contraction is the collapse of intermediate Level 2 apprenticeships, which historically served as the primary onboarding route into basic administrative and technical roles for school leavers. These intermediate roles fell from 43 percent of all starts in the 2017 to 2018 academic year to just 18.6 percent in 2024 to 2025.

Conversely, employer demand has migrated toward higher and degree apprenticeships, which now account for nearly 40 percent of all starts. This pivot reflects a broader training paradox wherein employers increasingly utilize levy funds to upskill existing older staff rather than hiring new entry-level trainees. In the 2024 to 2025 academic year, 51.3 percent of all apprenticeship starts were undertaken by individuals aged 25 and over (Department for Education, 2026). As routine cognitive tasks become commoditized by algorithms, employers are redirecting investments toward higher-level cognitive management and specialized digital skills, leaving a widening gap at the entry level.

### *B. Task Shifts and the Expected Impact of Artificial Intelligence*

To understand the distributional consequences of artificial intelligence, economic scholarship relies on the task-based approach. Breaking from canonical models of skill-biased technological change, which viewed technology merely as factor-augmenting, the task-based framework separates workers' skills from the discrete tasks they perform [7]. In the routine-biased technological change era of the late twentieth century, computer capital acted as a direct substitute for human workers in performing codifiable, routine tasks, effectively hollowing out middle-skill administrative and manufacturing jobs while complementing high-skill abstract reasoning [3].

Generative artificial intelligence, however, disrupts this historical pattern. Exhibiting the traits of a general-purpose technology, large language models excel at pattern recognition, implicit rule learning, and contextual synthesis, allowing them to automate non-routine cognitive tasks such as ideation, legal analysis, and content creation. Consequently, generative artificial intelligence poses the greatest task-exposure risk to high-income, highly educated knowledge workers.

Despite this high theoretical exposure, empirical evidence suggests artificial intelligence currently functions primarily as a labour-augmenting tool. By automating specific sub-tasks, artificial intelligence drives skill compression, disseminating tacit expertise to novice workers and forcing a reallocation of human labour toward higher-order strategic, decision-making, and interpersonal functions [8]. Under the theoretical framework of Acemoglu and Restrepo [4], [5], the aggregate macroeconomic outcomes of this technology depend on the balance between the displacement effect of automation and the reinstatement effect, which requires the continuous generation of new, labour-intensive tasks in which humans hold a comparative advantage.

As cognitive tasks become commoditized, educational and employment pathways are migrating toward the human premium, encompassing roles requiring high-touch empathy, specialized producing industries relying on physical craft, and ethical governance requiring human-in-command oversight [10].

## III. DATA AND LLM MODELLING

### *A. Data Sources and the ESCO Digital Framework*

This study utilizes vacancy data from the Department for Education Find an apprenticeship service. The dataset captures 619,629 adverts, corresponding to 942,798 individual apprenticeship jobs, posted between August 2018 and October 2025. The analysis restricts this universe to 492,818 adverts regulated under current Apprenticeship Standards, enabling the integration of complete regulatory data regarding occupational roles and educational levels.

To systematically quantify digital skill demand within these unstructured vacancies, the methodology integrates the European Skills, Competences, Qualifications and Occupations classification (ESCO). Specifically, the study extracts the digital skills domain, which is grounded in the European Digital Competence Framework for Citizens. By utilizing this poly-hierarchical ontology comprising 25 distinct digital competences rather than an arbitrary keyword list, the methodology ensures the extraction of statistically validated concepts, minimizing hallucinatory matching and correcting for occupational biases.

### *B. LLM Modelling: Mapping ESCO and Vacancies*

To evaluate occupational exposure to artificial intelligence, unstructured vacancy texts were mapped to the ESCO framework to identify digital skill intensity. A constraint-based domain association strategy was engineered using Distil-RoBERTa, a knowledge-distilled encoder model optimizing the balance between deep linguistic comprehension and computational speed [12], [13].

The raw vacancy descriptions underwent a rigorous natural language processing pipeline involving HTML stripping, punctuation removal, and Porter stemming. To minimize false positives, the semantic anchor of each ESCO skill was restricted exclusively to its alternate, technical labels. An exhaustive cosine similarity comparison was then executed between the vector representations of every vacancy and skill signature. A stringent threshold of 0.45 was applied, converting continuous similarity scores into binary digital skill intensity metrics for econometric modelling.

### *C. Generative AI and Task Extraction Modelling*

To evaluate task-level impacts, Google Gemini 1.5 Flash was utilized to dynamically generate occupation-specific taxonomies, producing 30 distinct, three-word technical tasks for each of the 463 Apprenticeship Standards. Due to severe computational constraints and API rate limits associated with processing massive text corpora via cloud-based generative models, the methodology pivoted to local, deterministic natural language processing for the extraction phase. The final extraction algorithm utilized set-based keyword proximity matching to verify if the discrete words of each generated task appeared within the aggregated annual vacancy corpus for specific occupations.

TABLE I  
DIGITAL SKILLS FOUND IN APPRENTICESHIP VACANCY ADVERTS

| Digital Skill                                                   | Adverts | Vacancies | Mean | Std. dev. | Min  | Max  |
|-----------------------------------------------------------------|---------|-----------|------|-----------|------|------|
| Solve technical problems                                        | 491,148 | 745,334   | 0.00 | 0.06      | 0.00 | 1.00 |
| Use e-services                                                  | 491,148 | 745,334   | 0.21 | 0.41      | 0.00 | 1.00 |
| Creatively use digital technologies                             | 491,148 | 745,334   | 0.13 | 0.34      | 0.00 | 1.00 |
| Evaluate data, information and digital content                  | 491,148 | 745,334   | 0.00 | 0.00      | 0.00 | 0.00 |
| Computer programming                                            | 491,148 | 745,334   | 0.00 | 0.04      | 0.00 | 1.00 |
| Identify digital competence gaps                                | 491,148 | 745,334   | 0.00 | 0.00      | 0.00 | 1.00 |
| Collaborate through digital technologies                        | 491,148 | 745,334   | 0.00 | 0.01      | 0.00 | 1.00 |
| Protect personal data and privacy                               | 491,148 | 745,334   | 0.00 | 0.03      | 0.00 | 1.00 |
| Share through digital technologies                              | 491,148 | 745,334   | 0.02 | 0.13      | 0.00 | 1.00 |
| ICT safety                                                      | 491,148 | 745,334   | 0.22 | 0.41      | 0.00 | 1.00 |
| Identify technological needs                                    | 491,148 | 745,334   | 0.45 | 0.50      | 0.00 | 1.00 |
| Manage data, information and digital content                    | 491,148 | 745,334   | 0.00 | 0.01      | 0.00 | 1.00 |
| Digital communication and collaboration                         | 491,148 | 745,334   | 0.00 | 0.01      | 0.00 | 1.00 |
| Integrate and re-elaborate digital content                      | 491,148 | 745,334   | 0.00 | 0.00      | 0.00 | 1.00 |
| Develop digital content                                         | 491,148 | 745,334   | 0.00 | 0.00      | 0.00 | 0.00 |
| Digital data processing                                         | 491,148 | 745,334   | 0.00 | 0.01      | 0.00 | 1.00 |
| Problem-solving with digital tools                              | 491,148 | 745,334   | 0.16 | 0.37      | 0.00 | 1.00 |
| Interact through digital technologies                           | 491,148 | 745,334   | 0.09 | 0.28      | 0.00 | 1.00 |
| Intellectual property regime of digital content                 | 491,148 | 745,334   | 0.00 | 0.00      | 0.00 | 1.00 |
| Manage digital identity                                         | 491,148 | 745,334   | 0.00 | 0.00      | 0.00 | 0.00 |
| Protect the environment from the impact of digital technologies | 491,148 | 745,334   | 0.00 | 0.00      | 0.00 | 0.00 |
| Protect health and well-being while using digital technologies  | 491,148 | 745,334   | 0.08 | 0.27      | 0.00 | 1.00 |
| Protect ICT devices                                             | 491,148 | 745,334   | 0.02 | 0.13      | 0.00 | 1.00 |
| Browse, search and filter data, information and digital content | 491,148 | 745,334   | 0.00 | 0.00      | 0.00 | 0.00 |
| Digital content creation                                        | 491,148 | 745,334   | 0.00 | 0.01      | 0.00 | 1.00 |

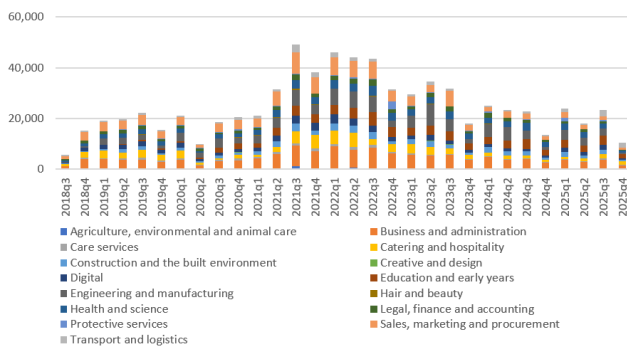


Fig. 1. Vacancies advertised on Find an apprenticeship, by quarter of closure date

#### D. Data Description

Overall vacancy volumes experienced severe contraction during the 2020 pandemic onset, followed by robust recovery peaking in 2022, and a subsequent gradual cooling through late 2025 (Fig. 1). Intermediate apprenticeships and business administration roles dominate traditional pathways (Fig. 2). Demand for the 25 digital skills is highly concentrated (Table I). Identifying technological needs appears in 45 percent of all vacancies, while information and communication tech-

TABLE II  
TOTAL DIGITAL SKILLS AND COMPETENCES PER ADVERT BY ROUTE

| Average of digital skills mentioned        | 2020 | 2022 | 2024 |
|--------------------------------------------|------|------|------|
| Agriculture, environmental and animal care | 0.55 | 1.16 | 0.91 |
| Business and administration                | 2.05 | 2.35 | 2.63 |
| Care services                              | 0.95 | 0.85 | 1.13 |
| Catering and hospitality                   | 0.24 | 0.25 | 0.24 |
| Construction and the built environment     | 1.04 | 1.30 | 1.56 |
| Creative and design                        | 1.40 | 1.29 | 0.86 |
| Digital                                    | 2.92 | 3.06 | 3.44 |
| Education and early years                  | 0.23 | 0.26 | 0.29 |
| Engineering and manufacturing              | 1.26 | 1.42 | 1.58 |
| Hair and beauty                            | 0.25 | 0.21 | 0.12 |
| Health and science                         | 1.10 | 0.71 | 0.53 |
| Legal, finance and accounting              | 1.71 | 2.06 | 2.16 |
| Protective services                        | 2.06 | 2.14 | 2.65 |
| Sales, marketing and procurement           | 1.61 | 2.06 | 2.39 |
| Transport and logistics                    | 1.34 | 1.44 | 1.69 |

nology safety is explicitly requested in 22 percent. Abstract digital creation skills exhibit near-zero presence. Digital skill intensity is compounding in technical sectors, with the digital route peaking at an average of 3.44 skills per advert in 2024 (Table II). The top five percent of apprenticeship standards most exposed to digital skills are heavily concentrated at the advanced, higher, and degree levels (Table III).

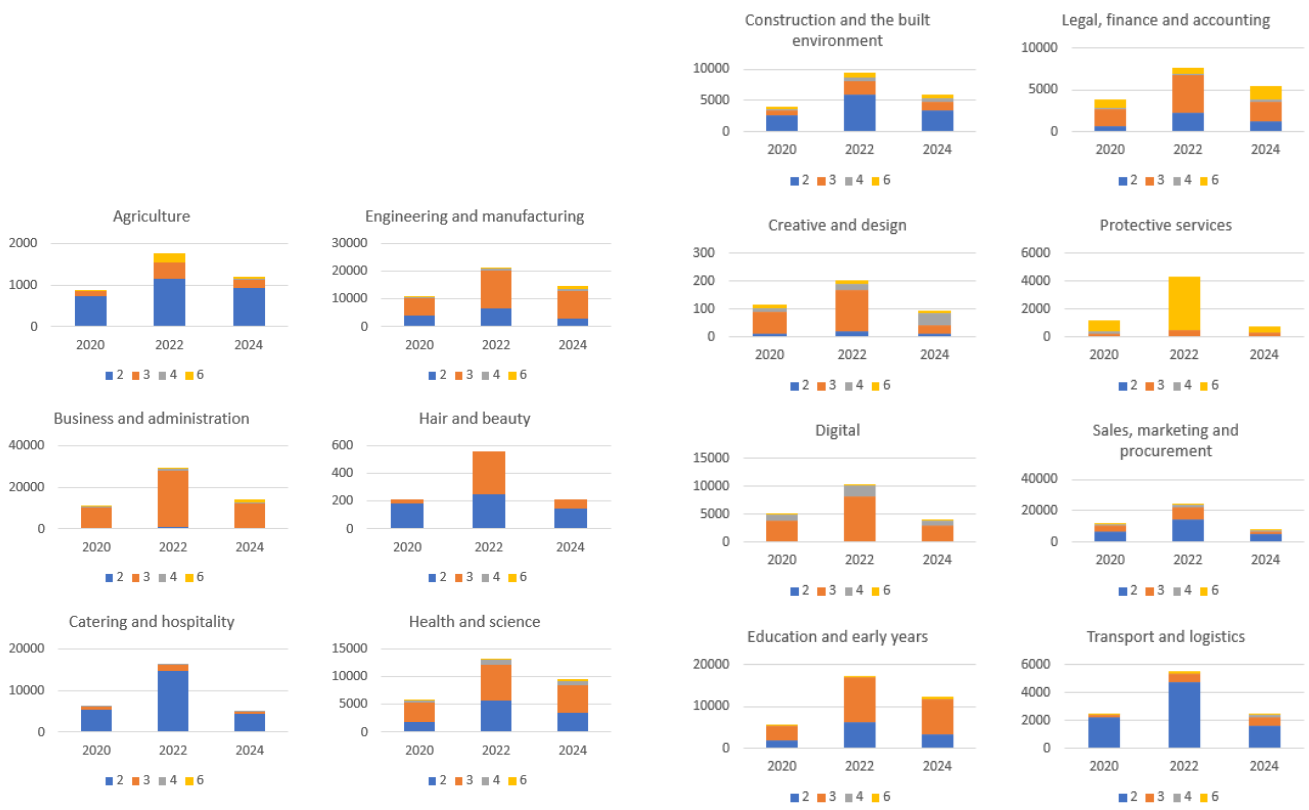


Fig. 2. Annual total vacancies by routes, levels and years

TABLE III  
TOP FIVE-PERCENTILE DIGITAL SKILLS APPRENTICESHIPS

| Standard Name                                     | Level        | Digital skills mentioned |
|---------------------------------------------------|--------------|--------------------------|
| Artificial intelligence (AI) data specialist      | Degree       | 3.00                     |
| Assistant technical director (visual effects)     | Higher       | 3.50                     |
| Broadcast and media systems technician            | Higher       | 4.92                     |
| Conveyancing technician                           | Higher       | 3.27                     |
| Cyber security technician                         | Advanced     | 2.97                     |
| Cyber security technologist                       | Higher       | 3.21                     |
| Cyber security technologist (2021)                | Higher       | 3.22                     |
| DevOps engineer                                   | Higher       | 2.95                     |
| Education technician                              | Advanced     | 5.33                     |
| Electrical power protection and plant c. engineer | Higher       | 3.67                     |
| Electro-mechanical engineer                       | Degree       | 2.85                     |
| Geospatial survey technician                      | Advanced     | 3.00                     |
| IT solutions technician                           | Advanced     | 3.53                     |
| Information communications technician             | Advanced     | 3.16                     |
| Infrastructure technician                         | Advanced     | 3.16                     |
| Investment operations administrator               | Intermediate | 6.00                     |
| Junior management consultant                      | Higher       | 3.22                     |
| Licensed conveyancer                              | Degree       | 6.00                     |
| Mammography associate                             | Higher       | 3.00                     |
| Post graduate engineer                            | Degree       | 3.00                     |
| Project controls professional                     | Degree       | 4.00                     |
| Revenues and welfare benefits practitioner        | Higher       | 2.88                     |
| Through life engineering services specialist      | Degree       | 3.00                     |
| Unified communications trouble shooter            | Higher       | 3.67                     |

#### IV. ECONOMETRIC MODELLING

This study investigates the empirical relationship between the widespread adoption of generative artificial intelligence and three key entry-level labour market outcomes: aggregate apprenticeship vacancy volumes, the intensity of required digital competencies, and shifts in specific occupational tasks. Utilizing a difference-in-differences strategy, the analysis defines the post-treatment period as 2023 and onwards, aligning with the market integration of advanced large language models. The primary treated group is strictly defined by sectors demanding a high magnitude of cognitive and digital skills, specifically the business, digital, protective services, and legal, finance and accounting routes. Conversely, the control group comprises vacancies in non-tangible human premium sectors reliant on physical craft or high-touch care, which are insulated from immediate algorithmic automation.

The econometric model testing hypotheses 1 and 3 at the level of occupation is specified as:

$$Y_{it} = \beta_0 + \beta_1(Post\_AI_t \times Exposed_i) + \gamma X_{it} + \delta_i + \theta_t + \epsilon_{it} \quad (1)$$

where  $Y_{it}$  represents job growth or tasks for occupation  $i$  at time  $t$ . The interaction term  $Post\_AI_t \times Exposed_i$  serves as the difference-in-differences estimator, capturing the shift in outcomes post-artificial intelligence introduction. The model includes fixed effects for the standard  $\delta_i$  and time  $\theta_t$ , further including specific route fixed effects  $X_{it}$ .

The econometric model evaluating Hypothesis 2 (digital skill intensity) is specified as:

$$Y_{it} = \beta_0 + \beta_1(Post\_AI_t \times Exposed_i) + \delta_i + \theta_t + \epsilon_{it} \quad (2)$$

where  $Y_{it}$  denotes the total number of digital competencies specified per individual advertisement  $i$  at time  $t$ , weighted by the number of available positions to reflect the true skill demand per job. To control for unobserved heterogeneity, the model incorporates time fixed effects ( $\theta_t$ ) alongside occupation fixed effects ( $\delta_i$ ). Estimations are conducted across the aggregate sample and subsequently stratified by educational level.

To validate the baseline estimates, two rigorous placebo tests are incorporated: a pre-artificial intelligence parallel trends test restricting data to 2021 and earlier, and a randomized sector assignment test which removes truly exposed sectors and randomly assigns treatment status to the remaining control sectors.

#### V. ARTIFICIAL INTELLIGENCE IMPACTS

##### A. Impact on Vacancy Volumes (Hypothesis 1)

The initial hypothesis posits that artificial intelligence disruption negatively impacts the total volume of job adverts in highly exposed sectors. Consistent with evidence that organizational friction and the delayed redesign of task structures inhibit immediate macroeconomic productivity shocks, the empirical results demonstrate no significant aggregate disruption to entry-level vacancy volumes.

The difference-in-differences estimator for the aggregate sample is negative but statistically indistinguishable from zero (Table IV). When stratified by educational level, the magnitude of the coefficient decreases as qualification requirements rise, yet none of the estimates achieve statistical significance. Consequently, the null hypothesis of no macroeconomic impact on the aggregate volume of apprenticeships cannot be rejected.

##### B. Impact on Digital Skill Requirements (Hypothesis 2)

The second hypothesis evaluates whether artificial intelligence shifts the intensity of digital competencies expected in entry-level roles. The primary model indicates that artificial intelligence exposed sectors inherently demand a higher baseline of digital competencies, and the post-treatment interaction reveals a statistically significant aggregate increase in total digital skill requirements (Table V).

However, robustness testing highlights critical nuances. Pre-period parallel trends tests indicate that intermediate Level 2 and advanced Level 3 apprenticeships exhibited significant divergence in skill trends well before the 2023 treatment period, invalidating causal attribution to generative artificial intelligence for lower tiers. In contrast, placebo models confirm the validity of the difference-in-differences estimator for Level 4, Level 5, and Degree Level 6 apprenticeships. The combined evidence credibly rejects the null hypothesis for higher educational tiers, demonstrating that artificial intelligence has driven a genuine, modest rise in digital skill requirements for advanced roles, reflecting skill complementarity rather than a hollowing-out effect.

##### C. Impact on Occupational Tasks (Hypothesis 3)

The third hypothesis asserts that artificial intelligence induces a significant shift or reduction in technical task density within highly exposed roles. Utilizing the deterministically extracted 30-task matrix, the econometric results fail to find pervasive evidence of task shifts. Across the majority of specified models, the interaction term for artificial intelligence exposure remains statistically insignificant (Table X and Table XI).

While isolated point estimates suggest a task shift occurring within higher Level 4 and 5 apprenticeships, scrutiny via pre-period robustness tests reveals that these specific occupational standards fail the parallel trends assumption (Table XII). These sectors exhibited significant differences in task trends prior to the advent of generative artificial intelligence, indicating that observed changes are manifestations of ongoing, long-term structural digitalization rather than an immediate artificial intelligence shock. Given the absence of robust coefficients, the null hypothesis regarding task shifts cannot be rejected.

#### VI. DISCUSSION AND POLICY IMPLICATIONS

The empirical analysis confirms that generative artificial intelligence has not precipitated an aggregate macroeconomic shock within the United Kingdom youth entry-level labour market. The observable decline in apprenticeship volumes

TABLE IV  
IMPACT ON GROWTH OF APPRENTICESHIP VACANCIES (LOGLINEAR)

|                              | (1)<br>All<br>(Sectors) | (2)<br>Level 2<br>Intermediate | (3)<br>Level 3<br>Advanced | (4)<br>Level 4-5<br>Higher | (5)<br>Level 6<br>Degree | (6)<br>All<br>(High ICT) |
|------------------------------|-------------------------|--------------------------------|----------------------------|----------------------------|--------------------------|--------------------------|
| Post-AI (time)               | -0.136<br>(0.103)       | -0.437*<br>(0.185)             | -0.0940<br>(0.169)         | 0.169<br>(0.213)           | 0.155<br>(0.232)         | -0.0817<br>(0.0938)      |
| AI Exposed Sector (affected) | 0.103<br>(0.166)        | 1.584*<br>(0.740)              | 0.973***<br>(0.281)        | 0.272<br>(0.258)           | 0.409<br>(0.325)         | -0.426<br>(0.346)        |
| DiD (time_affect)            | -0.108<br>(0.218)       | -1.177<br>(0.942)              | -0.398<br>(0.372)          | -0.312<br>(0.339)          | 0.0380<br>(0.424)        | 0.314<br>(0.468)         |
| Constant                     | 3.643***<br>(0.0781)    | 4.325***<br>(0.140)            | 3.899***<br>(0.128)        | 2.688***<br>(0.162)        | 2.639***<br>(0.180)      | 3.764***<br>(0.0707)     |
| N                            | 2071                    | 528                            | 735                        | 454                        | 354                      | 1937                     |

Note: Standard errors in parentheses. Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

TABLE V  
IMPACT ON NUMBER OF DIGITAL SKILLS MENTIONED PER ADVERT

|                   | (1)<br>All<br>(Sectors) | (2)<br>All<br>(Sectors) | (3)<br>Level 2<br>Intermediate | (4)<br>Level 2<br>Intermediate | (5)<br>Level 3<br>Advanced | (6)<br>Level 3<br>Advanced | (7)<br>Level 4-5<br>Higher | (8)<br>Level 4-5<br>Higher | (9)<br>Level 6<br>Degree | (10)<br>Level 6<br>Degree |
|-------------------|-------------------------|-------------------------|--------------------------------|--------------------------------|----------------------------|----------------------------|----------------------------|----------------------------|--------------------------|---------------------------|
| Post-AI (time)    | -0.0198***<br>(0.00512) | 0.0743***<br>(0.00480)  | 0.0251***<br>(0.00666)         | 0.0827***<br>(0.00593)         | -0.106***<br>(0.00837)     | 0.0559***<br>(0.00817)     | 0.0934***<br>(0.0245)      | 0.193***<br>(0.0226)       | -0.129***<br>(0.0228)    | 0.00808<br>(0.0233)       |
| AI Exposed Sector | 1.143***<br>(0.00642)   | -5.075<br>(4562.7)      | 0.886***<br>(0.0195)           | 1.888***<br>(0.226)            | 1.272***<br>(0.00881)      | 14.52<br>(8678.2)          | 0.650***<br>(0.0277)       | 0.0170<br>(1.730)          | -0.371***<br>(0.0234)    | 1.679<br>(1.409)          |
| DiD (time_affect) | 0.434***<br>(0.00946)   | 0.348***<br>(0.00876)   | 0.488***<br>(0.0302)           | 0.381***<br>(0.0264)           | 0.598***<br>(0.0127)       | 0.369***<br>(0.0122)       | 0.392***<br>(0.0386)       | 0.290***<br>(0.0363)       | 0.398***<br>(0.0302)     | 0.312***<br>(0.0307)      |
| Constant          | 0.998***<br>(0.00353)   | 0.729**<br>(0.237)      | 0.944***<br>(0.00430)          | 0.728***<br>(0.211)            | 1.044***<br>(0.00610)      | -8.518<br>(8678.2)         | 1.189***<br>(0.0183)       | 3.49e-11<br>(1.412)        | 1.263***<br>(0.0181)     | -1.20e-09<br>(1.150)      |
| Standard FE       |                         | Included                |                                | Included                       |                            | Included                   |                            | Included                   |                          | Included                  |
| N                 | 582824                  | 582824                  | 220125                         | 220125                         | 303918                     | 303918                     | 28935                      | 28935                      | 29846                    | 29846                     |

Note: Standard errors in parentheses. Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

TABLE VI  
ROBUSTNESS TEST: PRE-AI PARALLEL TRENDS

|                   | (1)<br>All              | (2)<br>All             | (3)<br>Level 2        | (4)<br>Level 2         | (5)<br>Level 3        | (6)<br>Level 3         | (7)<br>Level 4        | (8)<br>Level 4       | (9)<br>Level 6        | (10)<br>Level 6      |
|-------------------|-------------------------|------------------------|-----------------------|------------------------|-----------------------|------------------------|-----------------------|----------------------|-----------------------|----------------------|
| Post-AI (time)    | -0.0726***<br>(0.00755) | 0.0318***<br>(0.00737) | -0.00392<br>(0.00902) | 0.0897***<br>(0.00855) | -0.240***<br>(0.0132) | -0.0714***<br>(0.0132) | 0.412***<br>(0.0536)  | 0.135*<br>(0.0553)   | 0.121*<br>(0.0510)    | 0.179***<br>(0.0511) |
| AI Exposed Sector | 0.892***<br>(0.0107)    | -0.943<br>(1.478)      | 0.272***<br>(0.0399)  | 0.420<br>(0.267)       | 0.856***<br>(0.0151)  | -1.001<br>(10033.6)    | 1.005***<br>(0.0557)  | 1.610<br>(1.581)     | -0.350***<br>(0.0524) | -2.939<br>(1.779)    |
| DiD (time_affect) | 0.142***<br>(0.0131)    | 0.000564<br>(0.0127)   | 0.501***<br>(0.0463)  | 0.150**<br>(0.0477)    | 0.266***<br>(0.0183)  | 0.0821***<br>(0.0183)  | -0.453***<br>(0.0641) | -0.0778<br>(0.0649)  | 0.153*<br>(0.0611)    | -0.0614<br>(0.0601)  |
| Constant          | 1.044***<br>(0.00633)   | 0.910***<br>(0.274)    | 0.918***<br>(0.00748) | 0.877***<br>(0.246)    | 1.267***<br>(0.0111)  | 3.700<br>(15032.7)     | 0.749***<br>(0.0488)  | -3.82e-10<br>(1.369) | 1.098***<br>(0.0453)  | 3.821**<br>(1.258)   |
| Standard FE       |                         | Included               |                       | Included               |                       | Included               |                       | Included             |                       | Included             |
| N                 | 307320                  | 307320                 | 128534                | 128534                 | 153787                | 153787                 | 13122                 | 13122                | 11877                 | 11877                |

Note: Standard errors in parentheses. Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

TABLE VII  
ROBUSTNESS TEST 2: RANDOMIZED SECTORS

|                   | (1)<br>All             | (2)<br>All             | (3)<br>Level 2        | (4)<br>Level 2         | (5)<br>Level 3          | (6)<br>Level 3         | (7)<br>Level 4       | (8)<br>Level 4       | (9)<br>Level 6        | (10)<br>Level 6     |
|-------------------|------------------------|------------------------|-----------------------|------------------------|-------------------------|------------------------|----------------------|----------------------|-----------------------|---------------------|
| Post-AI (time)    | -0.0139**<br>(0.00537) | 0.0682***<br>(0.00480) | 0.0232**<br>(0.00784) | 0.0615***<br>(0.00686) | -0.0933***<br>(0.00798) | 0.0657***<br>(0.00720) | 0.125***<br>(0.0271) | 0.190***<br>(0.0241) | -0.105***<br>(0.0305) | 0.0182<br>(0.0293)  |
| AI Exposed Sector | 0.0399***<br>(0.00679) | 0.0183**<br>(0.00586)  | 0.0285**<br>(0.00928) | 0.00301<br>(0.00797)   | 0.0507***<br>(0.0107)   | 0.0399***<br>(0.00926) | 0.0736*<br>(0.0366)  | -0.00661<br>(0.0317) | 0.105*<br>(0.0442)    | 0.0897*<br>(0.0391) |
| DiD (time_affect) | -0.0190<br>(0.00987)   | 0.0216*<br>(0.00853)   | 0.00838<br>(0.0146)   | 0.0753***<br>(0.0125)  | -0.0418**<br>(0.0146)   | -0.0327*<br>(0.0127)   | -0.103*<br>(0.0488)  | 0.00858<br>(0.0423)  | -0.0803<br>(0.0556)   | -0.0333<br>(0.0495) |
| Constant          | 0.986***<br>(0.00372)  | 0.730***<br>(0.202)    | 0.936***<br>(0.00510) | 0.730***<br>(0.207)    | 1.029***<br>(0.00581)   | -0.0399<br>(1.197)     | 1.167***<br>(0.0203) | 1.007<br>(1.263)     | 1.231***<br>(0.0243)  | -0.0745<br>(1.244)  |
| Standard FE       |                        | Included               |                       | Included               |                         | Included               |                      | Included             |                       | Included            |
| N                 | 411683                 | 411683                 | 209434                | 209434                 | 171403                  | 171403                 | 17441                | 17441                | 13405                 | 13405               |

Note: Standard errors in parentheses. Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

TABLE VIII  
ROBUSTNESS TEST: PRE-AI PARALLEL TRENDS

|                   | (1)<br>All              | (2)<br>All             | (3)<br>Level 2        | (4)<br>Level 2         | (5)<br>Level 3        | (6)<br>Level 3         | (7)<br>Level 4        | (8)<br>Level 4       | (9)<br>Level 6        | (10)<br>Level 6      |
|-------------------|-------------------------|------------------------|-----------------------|------------------------|-----------------------|------------------------|-----------------------|----------------------|-----------------------|----------------------|
| Post-AI (time)    | -0.0726***<br>(0.00755) | 0.0318***<br>(0.00737) | -0.00392<br>(0.00902) | 0.0897***<br>(0.00855) | -0.240***<br>(0.0132) | -0.0714***<br>(0.0132) | 0.412***<br>(0.0536)  | 0.135*<br>(0.0553)   | 0.121*<br>(0.0510)    | 0.179***<br>(0.0511) |
| AI Exposed Sector | 0.892***<br>(0.0107)    | -0.943<br>(1.478)      | 0.272***<br>(0.0399)  | 0.420<br>(0.267)       | 0.856***<br>(0.0151)  | -1.001<br>(10033.6)    | 1.005***<br>(0.0557)  | 1.610<br>(1.581)     | -0.350***<br>(0.0524) | -2.939<br>(1.779)    |
| DiD (time_affect) | 0.142***<br>(0.0131)    | 0.000564<br>(0.0127)   | 0.501***<br>(0.0463)  | 0.150**<br>(0.0477)    | 0.266***<br>(0.0183)  | 0.0821***<br>(0.0183)  | -0.453***<br>(0.0641) | -0.0778<br>(0.0649)  | 0.153*<br>(0.0611)    | -0.0614<br>(0.0601)  |
| Constant          | 1.044***<br>(0.00633)   | 0.910***<br>(0.274)    | 0.918***<br>(0.00748) | 0.877***<br>(0.246)    | 1.267***<br>(0.0111)  | 3.700<br>(15032.7)     | 0.749***<br>(0.0488)  | -3.82e-10<br>(1.369) | 1.098***<br>(0.0453)  | 3.821**<br>(1.258)   |
| Standard FE       |                         | Included               |                       | Included               |                       | Included               |                       | Included             |                       | Included             |
| N                 | 307320                  | 307320                 | 128534                | 128534                 | 153787                | 153787                 | 13122                 | 13122                | 11877                 | 11877                |

Note: Standard errors in parentheses. Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

TABLE IX  
ROBUSTNESS TEST 2: RANDOMIZED SECTORS

|                   | (1)<br>All             | (2)<br>All             | (3)<br>Level 2        | (4)<br>Level 2         | (5)<br>Level 3          | (6)<br>Level 3         | (7)<br>Level 4       | (8)<br>Level 4       | (9)<br>Level 6        | (10)<br>Level 6     |
|-------------------|------------------------|------------------------|-----------------------|------------------------|-------------------------|------------------------|----------------------|----------------------|-----------------------|---------------------|
| Post-AI (time)    | -0.0139**<br>(0.00537) | 0.0682***<br>(0.00480) | 0.0232**<br>(0.00784) | 0.0615***<br>(0.00686) | -0.0933***<br>(0.00798) | 0.0657***<br>(0.00720) | 0.125***<br>(0.0271) | 0.190***<br>(0.0241) | -0.105***<br>(0.0305) | 0.0182<br>(0.0293)  |
| AI Exposed Sector | 0.0399***<br>(0.00679) | 0.0183**<br>(0.00586)  | 0.0285**<br>(0.00928) | 0.00301<br>(0.00797)   | 0.0507***<br>(0.0107)   | 0.0399***<br>(0.00926) | 0.0736*<br>(0.0366)  | -0.00661<br>(0.0317) | 0.105*<br>(0.0442)    | 0.0897*<br>(0.0391) |
| DiD (time_affect) | -0.0190<br>(0.00987)   | 0.0216*<br>(0.00853)   | 0.00838<br>(0.0146)   | 0.0753***<br>(0.0125)  | -0.0418**<br>(0.0146)   | -0.0327*<br>(0.0127)   | -0.103*<br>(0.0488)  | 0.00858<br>(0.0423)  | -0.0803<br>(0.0556)   | -0.0333<br>(0.0495) |
| Constant          | 0.986***<br>(0.00372)  | 0.730***<br>(0.202)    | 0.936***<br>(0.00510) | 0.730***<br>(0.207)    | 1.029***<br>(0.00581)   | -0.0399<br>(1.197)     | 1.167***<br>(0.0203) | 1.007<br>(1.263)     | 1.231***<br>(0.0243)  | -0.0745<br>(1.244)  |
| Standard FE       |                        | Included               |                       | Included               |                         | Included               |                      | Included             |                       | Included            |
| N                 | 411683                 | 411683                 | 209434                | 209434                 | 171403                  | 171403                 | 17441                | 17441                | 13405                 | 13405               |

Note: Standard errors in parentheses. Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

TABLE X  
IMPACT ON TOTAL NUMBER OF JOB TASKS FOUND IN ADVERTS (MODELLED WITH ROUTES AFFECTED)

|                   | (1)<br>All          | (2)<br>All           | (3)<br>Level 2<br>Inter. | (4)<br>Level 2<br>Inter. | (5)<br>Level 3<br>Adv. | (6)<br>Level 3<br>Adv. | (7)<br>Level 4-5<br>Higher | (8)<br>Level 4-5<br>Higher | (9)<br>Level 6<br>Degree | (10)<br>Level 6<br>Degree |
|-------------------|---------------------|----------------------|--------------------------|--------------------------|------------------------|------------------------|----------------------------|----------------------------|--------------------------|---------------------------|
| Post-AI (time)    | -1.015*<br>(0.416)  | -1.030***<br>(0.156) | -1.267<br>(0.714)        | -2.177***<br>(0.248)     | -0.997<br>(0.679)      | -0.868***<br>(0.251)   | -0.266<br>(1.002)          | 0.113<br>(0.434)           | 0.349<br>(0.783)         | 0.839*<br>(0.387)         |
| AI Exposed Sector | 5.608***<br>(0.616) | 8.698*<br>(3.455)    | 7.026***<br>(2.074)      | 1.667<br>(2.643)         | 8.183***<br>(0.972)    | 0.646<br>(3.664)       | 5.275***<br>(1.097)        | -1.738<br>(3.313)          | 4.125***<br>(1.029)      | -1.098<br>(2.873)         |
| DiD (time_affect) | 0.757<br>(0.886)    | 0.332<br>(0.331)     | 4.351<br>(3.267)         | 1.249<br>(1.144)         | -0.148<br>(1.399)      | -0.646<br>(0.513)      | 0.166<br>(1.532)           | -0.375<br>(0.662)          | 1.183<br>(1.450)         | 0.0984<br>(0.703)         |
| Constant          | 7.244***<br>(0.293) | -1.44e-10<br>(2.434) | 8.390***<br>(0.488)      | -1.30e-12<br>(2.289)     | 7.668***<br>(0.478)    | 0.868<br>(2.577)       | 5.365***<br>(0.730)        | 5.000*<br>(2.316)          | 3.259***<br>(0.587)      | 1.161<br>(2.007)          |
| Standard FE       |                     | Included             |                          | Included                 |                        | Included               |                            | Included                   |                          | Included                  |
| N                 | 1413                | 1413                 | 404                      | 404                      | 602                    | 602                    | 234                        | 234                        | 173                      | 173                       |

Note: Standard errors in parentheses. Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

TABLE XI  
IMPACT ON TOTAL NUMBER OF JOB TASKS FOUND IN ADVERTS (MODELLED AS STANDARDS AFFECTED)

|                   | (1)<br>All          | (2)<br>All          | (3)<br>Level 2<br>Inter. | (4)<br>Level 2<br>Inter. | (5)<br>Level 3<br>Adv. | (6)<br>Level 3<br>Adv. | (7)<br>Level 4-5<br>Higher | (8)<br>Level 4-5<br>Higher | (9)<br>Level 6<br>Degree | (10)<br>Level 6<br>Degree |
|-------------------|---------------------|---------------------|--------------------------|--------------------------|------------------------|------------------------|----------------------------|----------------------------|--------------------------|---------------------------|
| Post-AI (time)    | -0.849*<br>(0.371)  | -0.800*<br>(0.353)  | -1.059<br>(0.698)        | -1.190<br>(0.616)        | -1.160<br>(0.599)      | -0.957<br>(0.553)      | -0.0413<br>(0.774)         | 0.137<br>(0.669)           | 0.756<br>(0.669)         | 0.592<br>(0.638)          |
| AI Exposed Sector | 5.974***<br>(0.445) | 7.941***<br>(0.976) | 8.780***<br>(1.604)      | 19.08***<br>(2.875)      | 7.990***<br>(0.703)    | 12.44***<br>(1.791)    | 5.483***<br>(0.775)        | 4.477<br>(3.666)           | 4.677***<br>(0.730)      | -3.704<br>(4.425)         |
| DiD (time_affect) | 0.0238<br>(1.340)   | -0.889<br>(1.299)   | 0<br>(.)                 | 0<br>(.)                 | 3.118<br>(2.157)       | -0.582<br>(2.086)      | -1.818<br>(1.936)          | -3.639*<br>(1.688)         | -1.003<br>(1.833)        | -0.0506<br>(1.810)        |
| Constant          | 7.161***<br>(0.277) | 4.358***<br>(0.726) | 8.293***<br>(0.483)      | 5.599***<br>(0.867)      | 7.715***<br>(0.449)    | 1.837<br>(1.480)       | 5.273***<br>(0.643)        | 0.932<br>(3.503)           | 3.080***<br>(0.538)      | 3.704*<br>(1.698)         |
| Route FE          |                     | Included            |                          | Included                 |                        | Included               |                            | Included                   |                          | Included                  |
| N                 | 1413                | 1413                | 404                      | 404                      | 602                    | 602                    | 234                        | 234                        | 173                      | 173                       |

Note: Standard errors in parentheses. Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

TABLE XII  
ROBUSTNESS TEST FOR STANDARDS AFFECTED: PRE-AI PARALLEL TRENDS

|                   | (1)<br>All          | (2)<br>All          | (3)<br>Level 2<br>Inter. | (4)<br>Level 2<br>Inter. | (5)<br>Level 3<br>Adv. | (6)<br>Level 3<br>Adv. | (7)<br>Level 4-5<br>Higher | (8)<br>Level 4-5<br>Higher | (9)<br>Level 6<br>Degree | (10)<br>Level 6<br>Degree |
|-------------------|---------------------|---------------------|--------------------------|--------------------------|------------------------|------------------------|----------------------------|----------------------------|--------------------------|---------------------------|
| Post-AI (time)    | 0.829<br>(0.599)    | 0.965<br>(0.570)    | 0.353<br>(1.121)         | 0.825<br>(1.001)         | 1.280<br>(0.928)       | 1.424<br>(0.861)       | 1.237<br>(1.262)           | 1.724<br>(1.058)           | 0.445<br>(1.037)         | 0.108<br>(1.032)          |
| AI Exposed Sector | 5.616***<br>(0.660) | 7.497*<br>(3.534)   | 7.049**<br>(2.181)       | 19.56***<br>(3.948)      | 7.616***<br>(1.023)    | 12.97***<br>(2.517)    | 6.096***<br>(1.146)        | 6.445<br>(4.867)           | 4.088***<br>(0.990)      | 4.833<br>(2.824)          |
| DiD (time_affect) | -0.131<br>(1.728)   | -1.127<br>(1.740)   | 0<br>(.)                 | 0<br>(.)                 | 5.346<br>(2.761)       | 5.002<br>(2.952)       | -4.906*<br>(2.129)         | -7.947***<br>(1.800)       | -0.917<br>(2.984)        | -0.120<br>(3.001)         |
| Constant          | 6.646***<br>(0.527) | 3.780***<br>(1.084) | 8.132***<br>(0.967)      | 5.222***<br>(1.381)      | 6.758***<br>(0.817)    | 0.730<br>(2.111)       | 4.462***<br>(1.169)        | -1.724<br>(4.755)          | 2.972**<br>(0.933)       | 2.595<br>(2.407)          |
| Route FE          |                     | Included            |                          | Included                 |                        | Included               |                            | Included                   |                          | Included                  |
| N                 | 716                 | 716                 | 217                      | 217                      | 306                    | 306                    | 113                        | 113                        | 80                       | 80                        |

Note: Standard errors in parentheses. Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

stems from compounding structural factors, including shifting minimum wage frameworks, economic stagnation, and the systemic redirection of levy funding toward incumbent workers [14]. Rather than evidencing technological displacement or technical task reduction, the data reveals a modest increase in digital competency requirements exclusively for higher-tier apprenticeships. This indicates that advanced digital proficiency operates as a strong complement to artificial intelligence. Consequently, policy interventions should prioritize repairing collapsed intermediate training pipelines to equip young entrants with requisite digital literacies, rather than mitigating immediate algorithmic job destruction.

These null findings align directly with the macroeconomic productivity paradox associated with artificial intelligence [1], [2]. While micro-level experiments demonstrate performance gains in codifiable functions, translating these isolated efficiencies into aggregate macroeconomic shocks requires profound organizational restructuring. Because algorithms execute specific functions rapidly while organizations adapt slowly, this inherent friction significantly delays observable entry-level labour displacement. Furthermore, transitioning from automating routine functions to hard-to-learn tasks involving tacit knowledge yields diminishing marginal returns for total factor productivity [1]. To ensure inclusive economic growth, institutional incentives must steer technological development toward the reinstatement effect [5]. By prioritizing the creation of new, human-complementary tasks that demand sophisticated digital competencies, policymakers can ensure artificial intelligence functions as a mechanism for robust labour augmentation rather than widespread occupational substitution [6].

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#### GENERATIVE AI DISCLOSURE STATEMENT

During the preparation of this work, the authors used Google Gemini 1.5 Flash / Gemini 3.5 Flash to support the development of Python code for data processing and LLM implementation. Gemini and NotebookLM Pro were also used for editing and reducing the draft write-up, which did not affect the content. The authors take full responsibility for the content of this publication.

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