# New Rules, New Roles: Mandated Tax Digitalization and Accounting Labor Demand

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**Abstract:** This study uses the passage of Germany's eInvoicing mandate to examine how the digitalization of tax compliance affects accounting labor demand. Leveraging a large sample of job postings by German firms, we classify the digital sophistication each role requires with a large language model and compare monthly posting activity in firms' accounting functions with posting activity in their HR and marketing functions. Although overall accounting labor demand does not change, firms substitute away from less digitally sophisticated accounting roles toward more sophisticated roles that foster digital transformation. This substitution coincides with a shift in the seniority composition of accounting labor demand, with declines mainly in junior roles and increases mainly in senior roles. The shift occurs in permanent rather than temporary positions and appears concentrated among firms in less digitally intensive industries. Overall, our findings suggest that mandated digitalization reallocates accounting labor demand toward senior, digitally sophisticated employees.

**Keywords**: Accounting function; Compliance; Digitalization; eInvoicing; Job Postings; Taxation
**JEL Classification**: G38; H25; J23; J24; J44; M41; M48; O33

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# 1 INTRODUCTION

The digitalization of business environments is transforming labor demand within corporate accounting functions.[1] From a labor economics perspective, digitalization is a shock to the task composition of occupations. By changing which tasks workers perform, it changes which skills firms need, with potentially far-reaching consequences for hiring, training, and organizational structure. Yet despite the rapid spread of digital technologies, empirical evidence on how digitalization shapes labor demand within a given occupation remains sparse. This is partly because researchers rarely observe when a specific business process becomes digital, or which skills firms seek when they hire in response to digitalization. This study overcomes both obstacles by examining Germany's value-added tax (VAT) eInvoicing mandate, introduced as part of the Growth Opportunities Act. Because the mandate requires domestic business-to-business invoices to be exchanged in a structured electronic format, it digitalizes a core accounting process on a schedule set by the regulator rather than by firms. Moreover, because we observe the content of firms' job postings, we can trace how the skills firms demand within the accounting function change in response.

Our empirical analysis is guided by a task-based framework linking digitalization to the skills firms demand. Building on Acemoglu and Restrepo (2018, 2019), we distinguish between two effects. A displacement effect automates tasks in which accountants operate existing digital tools, such as manually entering invoice data into enterprise resource planning (ERP) systems, reducing demand for less digitally sophisticated roles. A reinstatement effect creates new tasks, such as designing, implementing, and integrating the systems that process structured data, raising demand for more digitally sophisticated roles. Together, the two effects predict a shift not from accounting toward digital expertise but along the spectrum of digital sophistication:

[1] We define digitalization as the redesign of business processes around machine-readable information and digitally integrated workflows (Goldfarb and Tucker, 2019).

from accountants who use digital systems toward accountants who develop and transform them.[2]

Whether this shift shows up in firms' hiring, however, is not obvious ex ante. If firms respond to the digitalization mandate mainly by retraining or reassigning their existing accounting staff, the shift could play out inside the firm. Specifically, employees in less digitally sophisticated roles are redeployed rather than let go, existing staff acquire the skills that new tasks require, and job postings change little. If instead firms lack the capacity to adjust internally, the shift should surface in the external labor market. Postings for less digitally sophisticated roles should decline as displacement takes hold, and postings for more digitally sophisticated roles should rise as firms recruit to fill the reinstated tasks. A third possibility is that firms outsource the affected work to tax advisors, shared-service centers, or software providers, in which case postings for less digitally sophisticated roles would decline without an offsetting rise in more sophisticated ones. How this compositional shift affects accounting labor demand is thus an empirical question.

To address our research question, we examine how accounting labor demand responds to the March 2024 passage of Germany's eInvoicing mandate.[3] Unlike voluntary technology adoption, which may reflect firms' own expectations, capabilities, or growth opportunities, the mandate requires affected firms to redesign their VAT compliance processes regardless of their prior level of digitalization. Because these processes reside in the accounting function, the demands fall primarily on accounting rather than on functions such as HR and marketing. Moreover, because firms must adapt their systems and staff before the obligations take effect,

[2] We use *roles* to refer to individual job postings. We classify a role as less digitally sophisticated if it involves routine use of enterprise systems but no digital transformation tasks, and as more digitally sophisticated if it involves designing or implementing digital transformation initiatives.

[3] The German parliament passed the Growth Opportunities Act in November 2023. Following mediation with the chamber representing Germany's 16 states, a revised version was approved on March 22, 2024, and the Act was promulgated on March 27, 2024. Practitioners we interviewed confirm that implementation began after the Act's passage in March 2024 (see Section 3.3).

hiring adjustments should begin at the reform's passage rather than at its later compliance deadlines.

We measure labor demand using job postings from Revelio Labs, which collects the near-universe of online job advertisements. Our sample comprises 101,847 accounting, HR, and marketing postings by 406 firms headquartered in Germany over a 16-month window surrounding the reform's passage. For each posting, we use GPT-6-Luna to classify the digital sophistication the role requires.[4] We then group roles into less digitally sophisticated roles, which involve routine use of enterprise systems, and more digitally sophisticated roles, which involve designing or implementing digital transformation (hereafter, low- and high-sophistication roles). To identify the reform's effects, we estimate a difference-in-differences specification at the firm-function-month level that compares posting activity in firms' accounting functions with that in their HR and marketing functions.[5] Firm-month fixed effects absorb firm-wide hiring shocks, and function fixed effects absorb time-invariant differences across functions. The key identifying assumption is that, absent the reform, accounting postings would have evolved in parallel with HR and marketing postings within the same firm.

We begin by examining whether the eInvoicing mandate alters firms' overall demand for accounting labor. Relative to HR and marketing, we do not find a significant change in accounting labor demand, either in the propensity to post any accounting job or in the number of postings. Once we distinguish postings by the digital sophistication they require, however, a clear substitution pattern emerges. Following the reform, the likelihood that firms post low-sophistication accounting jobs falls by about 8% relative to the sample mean, while the likelihood of posting high-sophistication accounting jobs rises by about 10%. This pattern is

[4] Appendix B provides the full prompt, the category definitions, and validation of the classification.

[5] We use HR and marketing as benchmark functions because, like accounting, they are corporate support functions that hire from comparable white-collar labor markets and are exposed to similar firm-wide digitalization trends, but they play no direct role in VAT compliance. We do not use functions such as procurement, sales, or IT as benchmarks because they may be directly affected by the mandate through invoice issuance, receipt, or system implementation.

inconsistent with firms absorbing the reform entirely within their existing workforce or simply outsourcing the affected work. Instead, these results suggest that, on average, firms recruit externally for different skills, shifting the typical accounting hire from operating the firm's accounting systems to reshaping them.

We next conduct three additional analyses to better understand the reallocation. First, the decline in low-sophistication postings comes primarily from junior roles, whereas high-sophistication postings shift from junior toward more senior roles, consistent with displacement falling on less-skilled workers and new tasks favoring more skilled ones (Acemoglu and Restrepo, 2018). Second, although firms could staff eInvoicing implementation with temporary workers (Section 3.3), the shift toward high-sophistication roles occurs in permanent positions, with no evidence of an effect on temporary accounting postings. Firms thus appear to treat mandated digitalization as a lasting change to the skills and seniority structure of their accounting function rather than as a one-off implementation project. Third, the effects appear concentrated among firms in less digitally intensive industries, as measured by Eurostat's Digital Intensity Index, consistent with digitally advanced firms already having the in-house capacity to absorb the reform.

Finally, we conduct a placebo test using firms headquartered in Switzerland, which is closely integrated with the German economy but has no business-to-business eInvoicing mandate and is not subject to European Union VAT legislation. Applying the same design around the March 2024 event date, we find no significant change in Swiss firms' accounting postings and no increase in their demand for high-sophistication roles, supporting the attribution of the shift toward digitally sophisticated accounting roles to the mandate.

We contribute to two streams of literature. First, we contribute to research on the real effects of accounting and tax regulation (e.g., Kanodia, 2007; Leuz and Wysocki, 2016; Minnis and Shroff, 2017; Lester and Olbert, 2025). Two strands of this literature are particularly

relevant. One examines the digitalization of compliance and reporting, showing that mandatory eInvoicing improves tax compliance and reduces evasion (Bellon et al., 2022; Heinemann and Stiller, 2025), digital financial reporting can raise productivity (Liu and Zhang, 2024), and new internal control requirements spur technology investments and a shift toward technology-based compliance roles at U.S. broker-dealers (Charoenwong et al., 2024). The other examines how tax policy and enforcement shape employment and the skills firms seek (Campello et al., 2024; Gallemore and Jacob, 2025). Following the Tax Cuts and Jobs Act, public accounting firms and corporate tax departments increased hiring of tax professionals (Daugherty, 2026; Giese et al., 2026). Similarly, IRS audits lead firms to expand their internal tax and general accounting staff (DePaul et al., 2026), and firms facing foreign tax scrutiny recruit specialized foreign tax experts (Munch et al., 2026). Yet these strands remain largely separate: studies of compliance digitalization focus on tax outcomes, whereas studies of tax-related labor demand focus on how greater complexity or scrutiny raises demand for tax and accounting expertise. We connect them by showing that mandated digitalization of tax compliance does not raise overall accounting labor demand but reallocates it across digital skill and seniority levels.

Second, we contribute to research on how technological change reshapes labor demand. A central insight of this literature is that technology rarely replaces workers wholesale but instead changes which tasks workers perform and which skills firms need (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018; Autor et al., 2024). For example, Hershbein and Kahn (2018) show that firms persistently raised skill requirements, particularly in routine-cognitive occupations. Other studies emphasize that technology pays off most when firms also invest in organizational capabilities and human capital (Bresnahan et al., 2002; Babina et al., 2024; Brynjolfsson et al., 2025). Other work links firms' demand for digital skills to employment growth (Balsmeier and Woerter, 2019; Jensen and Schneider, 2026) and examines how AI investments affect employment and skill demand (Fedyk et al., 2022; Berger

et al., 2024; Law and Shen, 2025; Böke et al., 2025; Choi and Xie, 2026; Gschossmann and Olbert, 2026). However, this work largely studies technologies firms choose to adopt, making it difficult to separate the effects of digitalization from firm characteristics that drive adoption.

Three recent working papers on digitalization within the accounting function are most closely related to our setting. Awyong et al. (2025) show that firm-level digitalization reduces demand for financial clerks while increasing digital-skill demand among financial specialists. Kim et al. (2026) show that accountant scarcity induces private firms to adopt accounting software, re-tasking accountants toward operations, finance, and management accounting activities. Downing (2026) shows that generative AI adoption at data-integrated firms reduces junior accountant hiring and reallocates remaining accounting work toward analytic tasks. Our study complements this work in three ways. First, rather than voluntary adoption, we study a regulatory mandate that imposes digitalization on a schedule set by the regulator. Second, rather than capturing whether roles require digital skills, we measure the level of digital sophistication required, distinguishing accountants who operate existing systems from those who develop and transform them. Third, we show that the reallocation occurs in permanent positions and moves demand toward more senior roles.

Our findings also inform managers, accounting professionals, students, and educators. Technological change is reshaping the accounting profession and firms' demand for accounting human capital (Friedman et al., 2026), and the global spread of mandatory eInvoicing and continuous transaction reporting is fundamentally changing accounting and tax processes (OECD, 2026). Our evidence that the eInvoicing mandate reduces demand for junior accounting roles, including those involving digital transformation, while increasing demand for more senior, digitally sophisticated roles raises the question of how entry-level accountants will acquire the hybrid skills that firms increasingly seek. This underscores the importance of accounting education that evolves alongside digital transformation and regulatory change.

# 2 HYPOTHESIS DEVELOPMENT

## 2.1 Theoretical Framework

Our research question lies at the intersection of occupational skill demand and technological change. We draw on these literatures to derive predictions about how the digitalization of tax compliance affects the digital sophistication firms seek in their accounting functions.

Technological change alters the relative productivity of different skills within an occupation, and thus the skills firms demand (Acemoglu and Autor, 2011). In Roy's (1951) model of occupational choice, workers sort into occupations according to their comparative advantage across skill dimensions, so the skill composition of an occupation reflects the returns the market places on particular skills. When digitalization changes the production technology of a job, these returns shift. As accounting processes move from paper-based or semi-manual workflows toward structured digital exchange formats, workers who can design and implement digital systems become more productive in accounting roles relative to those who can only operate existing ones. Firms should therefore update the profiles they seek, shifting demand toward more digitally sophisticated accounting roles.

The task-based framework of Acemoglu and Restrepo (2018, 2019) specifies how this shift occurs. It distinguishes between a *displacement* effect, in which technology substitutes for labor in specific tasks, and a *reinstatement* effect, in which technology creates new tasks that restore labor demand. The digitalization of accounting processes maps naturally onto both. On the displacement side, structured electronic workflows automate many routine tasks that previously required human effort in the accounting function, such as manually entering transaction data, cross-checking source documents against records, and transmitting data to counterparties or regulators. Autor et al. (2003) show that such routine cognitive tasks are those

most susceptible to computerization. To the extent that less digitally sophisticated accounting roles center on these tasks, digitalization should reduce the demand for them.

On the reinstatement side, new digital infrastructure creates tasks that did not previously exist. These include configuring and integrating digital compliance systems, ensuring interoperability with business partners' system architectures, and redesigning compliance workflows around structured data. These tasks are non-routine because they cannot be captured in predefined procedures: each implementation must be tailored to the firm's existing systems, its business partners, and the applicable compliance rules. They therefore require workers who understand both the logic of compliance requirements and the digital systems through which that logic is now implemented. The net prediction is not simply "fewer accountants" but a *compositional reallocation*: declining demand for less digitally sophisticated accounting roles alongside rising demand for more digitally sophisticated ones.

## 2.2 Hypotheses

The task-based framework implies that the digitalization of tax compliance shifts the digital sophistication firms require in their accounting functions. Displacement reduces demand for less digitally sophisticated accounting roles, and reinstatement increases demand for more digitally sophisticated accounting roles. Because the new tasks combine knowledge of compliance requirements with system design capabilities, they may not be easily filled by redeploying workers whose roles centered on the displaced tasks.

Whether this reallocation is visible in firms' hiring, however, is unclear ex ante. Firms may resolve it internally by retraining or reassigning existing staff, in which case the shift occurs within the existing workforce and job postings change little. Alternatively, firms may outsource the affected work to tax advisors, shared-service centers, or software providers, in which case postings for less digitally sophisticated roles decline without an offsetting rise in more sophisticated ones. Only if firms lack the capacity to adjust internally and instead recruit

externally should both effects surface in job postings. Because the digitalization of tax compliance falls primarily on the accounting function, we state the following hypotheses, in alternative form, relative to other corporate functions:

> **H1a: The digitalization of tax compliance reduces demand for less digitally sophisticated accounting roles relative to comparable roles in other corporate functions.**
>
> **H1b: The digitalization of tax compliance increases demand for more digitally sophisticated accounting roles relative to comparable roles in other corporate functions.**

## 3 INSTITUTIONAL BACKGROUND

We test our hypotheses using Germany's recent VAT eInvoicing mandate, which requires firms to digitalize a core tax compliance process. Section 3.1 describes the European VAT system, Section 3.2 describes regulatory initiatives to digitalize VAT compliance in Europe and Germany, and Section 3.3 summarizes insights from practitioner interviews.

### 3.1 The European Value-Added Tax (VAT) System

The European VAT system is a multi-stage consumption tax levied on the value added at each stage of production and distribution. At each stage, firms charge output VAT on their sales and deduct the input VAT paid on their purchases. Each firm therefore remits tax only on the value it adds, while total VAT collected equals the tax on final consumption.[6] Because firms can deduct input VAT only with a valid invoice, invoices are the central documentation for VAT deductions and enforcement, and firms rely on invoice-level information to report and reconcile their VAT liabilities. The VAT framework is harmonized across EU Member States, although statutory rates differ (e.g., 19% in Germany, 20% in France, and 22% in Italy), and the treatment of transactions varies depending on whether they are domestic or cross-border,

[6] For example, with a 19% VAT rate, a producer sells a good to a wholesaler for €100 plus €19 VAT and remits €19. The wholesaler sells it to a retailer for €110 plus €20.90 VAT and remits €1.90. The retailer sells it to a final consumer for €200 plus €38 VAT and remits €17.10. Total VAT remitted is €38, or 19% of the final sale price.

business-to-business (B2B) or business-to-consumer (B2C), and involve goods or services. Our setting focuses on domestic B2B transactions.

### 3.2 Digitalizing VAT Compliance

Given the central role of invoices, recent regulatory initiatives focus on digitalizing and standardizing them. eInvoicing refers to the electronic issuance, transmission, and receipt of invoice data in a structured, machine-readable format, such as Extensible Markup Language (XML). An unstructured PDF alone does not qualify as an eInvoice. Structured eInvoices instead allow automated validation and direct exchange across firms' enterprise resource planning (ERP) systems, accounting software, and tax authorities' reporting infrastructures, eliminating manual data entry and optical character recognition (OCR)-based extraction. At the same time, eInvoicing creates new demands. Firms must validate and correctly classify transaction-level data as it is exchanged, which requires tighter integration of accounting, tax, and IT systems.

At the EU level, Directive 2014/55/EU, adopted in April 2014, requires public authorities to accept structured eInvoices in public procurement (business-to-government, B2G) and laid the groundwork for a common European standard. Building on this foundation, the European Commission proposed the VAT in the Digital Age (ViDA) initiative in December 2022 to modernize VAT reporting, reduce fraud, and improve compliance through digital data exchange. ViDA was adopted in March 2025 and entered into force on April 14, 2025. It provides a harmonized framework that culminates in mandatory structured eInvoicing and digital reporting for cross-border B2B transactions within the EU by July 2030, while allowing Member States to introduce domestic mandates earlier.

Germany is a prominent early adopter. In July 2023, the EU granted Germany a derogation authorizing mandatory structured eInvoicing for domestic transactions ahead of the EU-wide rollout. This enabled the passage of the Growth Opportunities Act

(*Wachstumschancengesetz*) in March 2024. The mandate is phased in asymmetrically. Since January 2025, firms must be able to *receive* structured eInvoices for domestic B2B transactions. Subject to statutory exemptions, the *issuance* obligation applies from January 2027 to firms with prior-year turnover exceeding €800,000 and from January 2028 to the remaining covered firms (Figure 1, Panel A). Because the Act fixed the compliance timeline and technical requirements, firms could anticipate their obligations well before the mandate took effect and had a strong incentive to begin adjusting their accounting workforce immediately after passage. We therefore treat the March 2024 passage, rather than the later implementation dates, as the relevant event.

[Insert Figure 1 here]

Figure 1, Panel B, illustrates how the transition from document-based invoicing to structured eInvoicing changes accounting workflows. Under document-based invoicing, accounting staff capture, verify, and process invoice data largely through manual work and routine systems use. Under eInvoicing, structured data flow directly into the buyer's ERP system, shifting skill requirements toward system integration, enterprise systems configuration, and process automation. This illustrates the mechanism underlying our hypotheses: declining demand for less digitally sophisticated accounting roles alongside rising demand for more digitally sophisticated ones.

Finally, the reform's burden varies across functions within the same firm. Because the mandate governs invoice processing and VAT reporting, its operational demands fall primarily on the accounting function, which is responsible for VAT compliance, invoice validation, and audit documentation. These demands include systems integration, structured data pipelines, and process redesign. Functions such as HR and marketing perform no invoicing or VAT tasks and are therefore largely unaffected by the reform. This within-firm variation in exposure,

driven by the functional scope of the regulation rather than by differences across firms, underlies our research design.

### 3.3 Insights from Practice

To understand how firms implement the mandate, we conducted five interviews with practitioners from the automotive, aviation, manufacturing, insurance, and consulting sectors, covering small and medium-sized enterprises as well as large corporations. Interviewees include managing directors, heads of tax, tax managers, and consulting partners advising firms on eInvoicing implementation.

The interviews corroborate our choice of event date. Although firms monitored the earlier ViDA discussions, implementation began only after the German law passed in March 2024, because internal budgets required a binding legal decision. As one practitioner explains, "*No CFO in the world will approve anything until there is a binding decision in writing*." Once the law was enacted, firms organized implementation as a single project covering both inbound and outbound eInvoicing, rather than as separate initiatives aligned with each compliance deadline. Large corporations in particular describe the reform as a significant compliance and organizational project requiring coordination across several corporate functions.

The interviews also suggest that firms' responses depend on their existing capabilities. Firms with established tax functions and compatible ERP landscapes may implement the reform internally, whereas firms without these capabilities are more likely to seek skills externally. These accounts underscore that the effect of digitalizing tax compliance on external accounting labor demand is unclear ex ante.

# 4 RESEARCH DESIGN

## 4.1 Empirical Strategy

To examine how the passage of Germany's eInvoicing mandate affects accounting labor demand, we exploit within-firm variation in exposure to the regulation across corporate functions. Because the mandate governs invoice processing and VAT reporting, its operational burden falls primarily on the accounting function, whereas functions such as human resources (HR) and marketing are largely unaffected (Section 3.2). We therefore estimate a difference-in-differences specification at the firm-function-month level, in which firms' accounting functions form the treatment group and their HR and marketing functions form the control group. We define the treatment period by the passage of the Growth Opportunities Act in March 2024, consistent with the discussion in Sections 3.2 and 3.3. Specifically, we estimate:

$$Posting_Behavior_{itd} = \beta_0 + \beta_1 Acct_d + \beta_2 Post_t + \beta_3 Acct_d \times Post_t + \text{FE} + \varepsilon_{itd} \quad (1)$$

*Posting_Behavior* is one of two proxies for labor demand. *Postings_Binary* is an indicator variable equal to one if firm *i* posts at least one job ad for function *d* in month *t*, and zero otherwise. *ihs(Postings_Count)* is the inverse hyperbolic sine of the number of postings by firm *i* for function *d* in month *t*. For tests using *ihs(Postings_Count)*, we restrict the sample to firm-months with at least one posting in any of the three functions. To test H1a and H1b, we estimate Equation (1) separately for postings with low and high digital sophistication (Section 4.3).

*Acct* is an indicator variable equal to one for the accounting function and zero for HR and marketing. *Post* is an indicator variable equal to one from March 2024 onward and zero otherwise. The coefficient of interest, $\beta_3$, captures the change in accounting labor demand after the reform relative to the change in HR and marketing labor demand within the same firm.

All specifications include firm-month and function fixed effects, which absorb the standalone terms *Acct* and *Post*. Firm-month fixed effects absorb time-varying shocks that

affect hiring across all of a firm's functions, such as changes in its growth prospects. Function fixed effects absorb time-invariant differences in posting activity across functions. Identification therefore comes from changes in labor demand across functions within the same firm and month. The key identifying assumption is that, absent the reform, accounting postings would have evolved in parallel with HR and marketing postings within the same firm. We assess this assumption using a dynamic specification in Section 5.2. We cluster standard errors by firm-function to account for serial correlation in residuals over time and winsorize continuous variables at the 1st and 99th percentiles. Appendix A provides variable definitions.

### 4.2 Sample Selection

Our initial sample comprises 687 firms headquartered in Germany with data available in both Compustat Global and Revelio Labs. Table 1 summarizes the sample selection. We exclude firms in employment services (NAICS 5613) and in accounting, tax preparation, bookkeeping, and payroll services (NAICS 5412). These firms advertise roles on behalf of clients or as part of their own service offerings, so their postings reflect their product markets rather than their own labor demand. We also exclude firms whose products are likely to respond directly to the reform, namely firms in software publishing (NAICS 5112/5132), data processing and hosting (NAICS 5182), and computer systems design (NAICS 5415) whose business descriptions indicate that they provide ERP, CRM, accounting, tax, payroll, HR, compliance, or documentation systems.[7] Because these industries are broad, we limit this exclusion to firms with such business descriptions rather than excluding the industries entirely. These exclusions reduce the sample to 655 firms.

[7] Specifically, we search business descriptions for mentions of enterprise resource planning (ERP), SAP, Microsoft Dynamics 365, or enterprise software, applications, solutions, and content or information systems; customer relationship management (CRM); accounting, financial reporting, or financial management software, tax software, tax incentive or tax compliance management, payroll, and bookkeeping; human resources (HR) or human capital management, workforce and talent management, time and attendance systems, and personnel management; compliance software, solutions, or management platforms, governance, risk, and compliance (GRC) offerings, RegTech, whistleblower systems, and GDPR compliance; and document management, content management, digital archiving, and electronic invoicing.

[Insert Table 1 here]

Our sample period spans the 16 months from July 2023 through October 2024. It is centered on the March 2024 passage of the Growth Opportunities Act and ends before the first compliance obligation took effect in January 2025. To ensure that sample firms recruit through public job postings, we require each firm to post at least one accounting, HR, or marketing job ad during this period, which reduces the sample to 423 firms. We impose this requirement jointly across the three functions rather than function by function to avoid conditioning on posting activity that the reform could itself affect. The requirement excludes firms that do not recruit through public postings (e.g., firms relying on internal transfers, recruiters, or informal channels), so our findings apply to firms that engage in at least some public recruiting.

We then refine the postings data. We exclude postings with no more than 1,000 characters, which typically contain too little information for reliable classification. We also exclude postings that our classification identifies as noise, whose content does not match their assigned corporate function, or that receive no digital sophistication category (Appendix B). Firms with no remaining postings drop out, yielding a final sample of 406 firms and 101,847 postings. We aggregate postings to the firm-function-month level and set posting activity to zero in firm-function-months without observed postings, resulting in 19,488 observations (406 firms × 3 functions × 16 months).

### 4.3 Measuring Functional Labor Demand and Digital Sophistication

We use job postings as a timely, forward-looking measure of function-specific labor demand that also reveals the skills firms seek. Our data come from Revelio Labs, which collects the near-universe of publicly posted job ads from major online job boards (e.g., Indeed, LinkedIn, and regional aggregators) and company career websites, and removes duplicate postings across sources. For each posting, the data include the raw title and job description,

posting and removal dates, seniority level, job location, and an occupation code following the O*NET-SOC taxonomy.[8]

Because our identification strategy exploits within-firm variation across functions, we retain postings in three corporate functions, assigned based on O*NET-SOC codes: (i) accounting and tax, (ii) HR, and (iii) marketing. Accounting and tax positions include core accounting and compliance roles, such as accountants and auditors, controllers and treasurers, budget analysts, tax specialists, and billing, bookkeeping, and accounting clerks. HR positions comprise occupations related to personnel management, compensation, and payroll. Marketing positions include roles in advertising, promotions, public relations, and marketing management.[9] We exclude postings whose descriptions contain no more than 1,000 characters, because such postings carry little information about the underlying job. As an additional quality check, our LLM classification (described below) flags postings that are noise rather than genuine job ads, or whose content does not match their assigned function, and we remove these postings.

We then classify each posting by the digital sophistication required to fill the position. For each posting, we provide the job description to GPT-6-Luna, a large language model (LLM), and ask it to evaluate the digital sophistication required for the position. Appendix B describes the prompt design and its validation. Compared with a human-coded benchmark of 1,000 randomly drawn postings, the LLM's highest assigned category matches the human coding in 91.3% of cases. For our main analyses, we distinguish two levels. Postings with *low digital sophistication* require routine transactional use of enterprise platforms within

[8] The O*NET-SOC taxonomy is the occupational classification system used by the U.S. Department of Labor's Occupational Information Network (O*NET). It extends the U.S. Standard Occupational Classification (SOC) system to support O*NET's detailed occupational information.

[9] Specifically, accounting and tax positions include O*NET-SOC codes 11-3031.01, 13-2011.00, 13-2031.00, 13-2082.00, 43-3011.00, 43-3021.00, and 43-3031.00; HR positions include 11-3111.00, 11-3121.00, 13-1071.00, 13-1075.00, 13-1141.00, 43-3051.00, and 43-4161.00; and marketing positions include 11-2011.00, 11-2021.00, 11-2032.00, 13-1161.00, and 27-3031.00.

predefined workflows but involve no digital transformation tasks. Postings with *high digital sophistication* require leading, designing, or implementing system rollouts, process automation, or enterprise systems configuration. Appendix C provides example postings for each level.

Finally, we aggregate posting-level data by firm, function, and calendar month of the posting date to construct the variables described in Section 4.1, both for all postings and separately by level of digital sophistication. For our additional analyses, we further split postings by seniority, using Revelio Labs' seniority classification, and by employment type, using the LLM's classification of each posting's employment arrangement (Appendix B).

# 5 RESULTS

## 5.1 Descriptive Statistics

Table 2 presents descriptive statistics. Panel A shows that the sample is balanced: each of the three functions contributes 3,248 firm-months in both the eight pre-treatment and eight post-treatment months. Panel B shows the distribution of sample firms across two-digit NAICS industries. Manufacturing firms account for almost half of the sample (45.6%), followed by finance and insurance (13.3%) and information (8.6%), consistent with the distribution in the broader universe of German firms covered in Compustat Global.

[Insert Table 2 here]

Panel C reports summary statistics for our main variables. Firms post at least one job ad in about 41% of firm-function-months. Postings with low digital sophistication are roughly twice as common as those with high digital sophistication (31% versus 15% of firm-function-months). Accounting is the most active function: firms post accounting jobs in 49% of firm-months, compared with 38% for HR and 36% for marketing, and post more accounting jobs per active month on average (9.6, versus 7.0 for HR and 6.2 for marketing).

[Insert Figure 2 here]

Figure 2 shows the share of postings with low and high digital sophistication in each function. Accounting postings are the most likely to involve high digital sophistication: about 20.8% are high-sophistication, compared with 15.2% in HR and only 4.1% in marketing. The comparably low share of high-sophistication postings in marketing reflects a larger share of marketing postings that fall into neither group. Low-sophistication postings are common in all functions, ranging from 32.4% in marketing to 47.3% in accounting. Because both levels appear in all three functions, we can compare accounting postings with HR and marketing postings at the same level of sophistication.

### 5.2 Accounting Labor Demand and Digital Sophistication

Table 3 presents the results from estimating Equation (1). Columns (1)–(3) use *Postings_Binary* as the dependent variable, and Columns (4)–(6) use *ihs(Postings_Count)*. We begin with overall labor demand, irrespective of digital sophistication, in Columns (1) and (4). Relative to HR and marketing, neither the likelihood that firms post accounting jobs nor the number of accounting postings changes significantly after the passage of the eInvoicing mandate.

[Insert Table 3 here]

This null result could reflect either no response to the reform or offsetting changes within the accounting function. To distinguish between these possibilities, we estimate Equation (1) separately for postings with low digital sophistication (Columns (2) and (5)) and high digital sophistication (Columns (3) and (6)). Consistent with H1a, the likelihood that firms post low-sophistication accounting jobs declines by 2.43 percentage points relative to HR and marketing (Column (2); $p = 0.046$), or about 8% of the sample mean of 30.7%. The corresponding coefficient in Column (5) is negative but statistically insignificant (−0.0193). The reform thus reduces the likelihood that firms post low-sophistication accounting jobs at

all, but in firm-months with posting activity, it does not significantly reduce the number of such postings.

Consistent with H1b, demand for high-sophistication accounting roles increases. The likelihood that firms post such jobs rises by 1.57 percentage points (Column (3); p = 0.093), or about 10% of the sample mean of 15.4%. The number of high-sophistication accounting postings also increases (Column (6): 0.0612; p = 0.017). Evaluated at the sample mean, this estimate implies an increase of about 16%.[10] Together, these results indicate that firms respond to mandated digitalization by reallocating demand within the accounting function. They become less likely to seek accountants who operate existing systems and more likely to seek accountants who can lead and implement digital change. The reform thus changes the profile of the typical accounting candidate rather than the overall level of accounting labor demand.

Our difference-in-differences design assumes that, absent the reform, accounting postings would have evolved in parallel with HR and marketing postings. To assess this assumption, we re-estimate Equation (1), replacing *Post* with monthly indicators interacted with *Acct* and using February 2024, the last month before the Act's passage, as the reference period. Figure 3 plots the coefficients and 90% confidence intervals for *Postings_Binary* (Panels A and B) and *ihs(Postings_Count)* (Panels C and D).

[Insert Figure 3 here]

In the pre-treatment period, the coefficients fluctuate around zero and are statistically insignificant in all months. After passage, the estimates shift in the predicted directions. For low-sophistication postings, the coefficients for the likelihood of posting are negative in nearly every post-treatment month, with the largest declines toward the end of the sample period (Panel A). The decline in posting counts, by contrast, is concentrated in March and April 2024

[10] Because the dependent variable is ihs-transformed, we convert the coefficient into a percentage change by back-transforming at the sample mean of the transformed outcome ($\bar{y} = 0.415$): $[\sinh(\bar{y} + \beta) - \sinh(\bar{y})] / \sinh(\bar{y}) \approx 16\%$.

and fades thereafter (Panel C), consistent with the insignificant estimate in Table 3, Column (5). For high-sophistication postings, both the likelihood of posting (Panel B) and the number of postings (Panel D) increase after passage, and the increase grows over time, with the largest effects in the second half of the post-treatment period. Overall, we find no evidence of differential pre-trends between the treatment and control functions, and the gradual build-up of post-treatment effects is consistent with firms adjusting their hiring as they prepare for the compliance obligations.

### 5.3 Accounting Labor Demand by Seniority

Digitalization may also change the seniority profile of accounting labor demand. The new tasks it creates require not only advanced digital skills but also substantive accounting and tax knowledge. Such hybrid expertise is likely scarce, because it spans domains that have traditionally been separate in professional training, and firms may therefore source it through more experienced hires rather than through junior positions or internal training alone. This prediction is also consistent with the task-based framework, in which displacement tends to fall on less-skilled workers and new tasks tend to favor more skilled ones (Acemoglu and Restrepo, 2018). We therefore examine whether the substitution documented in Table 3 is concentrated at particular seniority levels.

We use Revelio Labs' seniority classification, which distinguishes seven ordinal levels ranging from entry-level to senior executive positions. For interpretability, we pool these into three groups: junior (levels 1–2), associate- to director-level (levels 3–5), and executive (levels 6–7). Figure 4 shows the distribution of these groups by function. Junior positions account for about half of accounting postings (52.0%), compared with 60.3% in HR and 55.3% in marketing. Executive positions are rare in all functions (0.8% to 1.4% of postings), so we exclude them and compare junior with more senior positions.

[Insert Figures 4 & 5 here]

Figure 5 shows how seniority varies with digital sophistication in accounting postings. Among junior accounting postings classified as low or high sophistication, about 79.0% require low digital sophistication, whereas high-sophistication postings account for about 40.7% of associate- to director-level postings (compared with 21.0% of junior postings). This positive correlation between seniority and digital sophistication suggests that a shift toward more digitally sophisticated accounting roles may also shift the seniority composition of accounting labor demand.

[Insert Table 4 here]

Table 4 tests this conjecture by re-estimating Equation (1) separately for junior positions (Panel A) and associate- to director-level positions (Panel B). Three patterns emerge. First, the decline in low-sophistication accounting postings is concentrated among junior positions, where the likelihood of posting falls by 2.40 percentage points. Second, the increase in high-sophistication accounting postings occurs among more senior positions, where both the likelihood and the number of postings rise significantly. Third, demand for junior high-sophistication roles actually declines, though by less than it rises at more senior levels. Taken together, these results indicate that the reform shifts accounting labor demand toward more senior positions: firms hire fewer juniors to operate existing systems and assign responsibility for transforming those systems to more senior roles.

### 5.4 Accounting Labor Demand by Employment Type

The shift toward high-sophistication accounting roles could reflect two different adjustments. On the one hand, firms may treat the reform as a one-off implementation project. Consistent with practitioners' descriptions of the reform as a significant compliance and organizational project (Section 3.3), firms could bring in time-limited capacity to configure systems and redesign processes and let it lapse once implementation is complete. On the other hand, firms may view the reform as a lasting change to how the accounting function operates

and build the required skills into their permanent workforce. If the shift is transitory, it should appear in temporary positions. If it reflects a lasting restructuring of the accounting function, it should appear in permanent positions.

To distinguish between these explanations, we use the LLM to classify each posting's employment type (Appendix B). We treat contract, temporary, internship, and apprenticeship positions as temporary, since all are time-limited by design, and all other postings as permanent.[11] This includes postings that do not state an employment type, which make up more than half of the sample. Because open-ended employment is the legal default in Germany, fixed-term positions are typically identified as such in the posting. As Figure 6 shows, most postings in all three functions are for permanent positions, especially in accounting (89% versus 77% in HR and 67% in marketing), mainly because HR and marketing post more internships and apprenticeships.[12]

[Insert Figure 6 & Table 5 here]

Table 5 presents the results. For temporary positions (Panel A), we find no evidence that the reform changes accounting labor demand: all four coefficients are small and statistically insignificant. For permanent positions (Panel B), the results closely mirror our main findings. Firms become 2.23 percentage points less likely to post permanent low-sophistication accounting jobs ($p = 0.075$), close to the 2.43 percentage points in Table 3. For permanent high-sophistication jobs, the likelihood of posting rises by a similar magnitude to our main estimate, though not significantly ($p = 0.117$), while the number of postings increases significantly ($p = 0.033$), by about 14% relative to the implied baseline.

[11] While the prompt asks for a single primary employment type, the LLM occasionally assigns multiple employment types; in these cases, the temporary type takes precedence.

[12] These compositional differences raise the concern that our main results reflect differences in the types of positions firms advertise across functions rather than changes in accounting labor demand. However, because our results concentrate in permanent positions, and we find no effects for the temporary positions in which the functions differ most, such compositional differences are unlikely to explain our findings.

Overall, the shift toward more digitally sophisticated accounting labor appears in permanent rather than temporary positions. This pattern is more consistent with firms permanently restructuring the skills of their accounting function than with time-limited staffing for implementation.

### 5.5 Accounting Labor Demand by Industry Digital Intensity

The reform's effect on the accounting function likely depends on how digitalized a firm's operations already are. Firms in digitally intensive industries are more likely to have structured electronic invoicing workflows in place before the reform, so complying with the mandate requires less restructuring of their accounting function. Firms in less digitalized industries face a larger gap between existing practice and the new requirements and are less likely to have the internal capacity to close it by reallocating existing staff. Practitioners we interviewed describe a similar pattern: firms with established tax functions and compatible ERP landscapes may implement the reform internally, whereas others are more likely to seek skills externally (Section 3.3). We therefore expect the shift in accounting labor demand to be concentrated among firms in less digitally intensive industries.

We measure industry digital intensity using Eurostat's Digital Intensity Index (DII), which is based on the annual EU survey on ICT usage in enterprises. The DII scores each surveyed enterprise on twelve indicators of digital technology use, such as the use of ERP or CRM software, cloud computing, and AI. For each industry, we use the share of German enterprises with high or very high digital intensity in the 2023 survey wave, the last wave before the passage of the Growth Opportunities Act. Because the survey does not cover financial services and several other service industries, the measure is available for 340 of our 406 sample firms. We split these firms at the sample median and re-estimate Equation (1) separately for each group.

Table 6 presents the results. For firms in less digitally intensive industries (Panel A), the results mirror our main findings but are larger. These firms become 4.45 percentage points less likely to post low-sophistication accounting jobs ($p = 0.017$) and 2.54 percentage points more likely to post high-sophistication ones ($p = 0.074$), and their number of high-sophistication postings rises significantly. For firms in more digitally intensive industries (Panel B), none of the coefficients is significant. Notably, these firms show a similar, though statistically insignificant, decline in low-sophistication postings but essentially no increase in high-sophistication postings.

[Insert Table 6 here]

Panel B also reports p-values from tests of equal coefficients across the two groups. None of the differences is statistically significant at conventional levels, which is unsurprising because tests of differences between subsample estimates have considerably less power than tests of each estimate against zero. We therefore interpret this evidence as suggestive. Nonetheless, the pattern is consistent with firms in more digitally intensive industries being better prepared for the digitalization of tax compliance. Their estimated decline in low-sophistication postings resembles that of other firms, but they do not increase external hiring for high-sophistication roles, suggesting that they meet the new tasks with existing staff.

### 5.6 Placebo Test

Our identification strategy assumes that, absent the reform, accounting labor demand would have evolved similarly to HR and marketing labor demand within the same firm. Firm-month fixed effects absorb shocks common to all of a firm's functions, but they cannot rule out developments coinciding with the passage of the Growth Opportunities Act that specifically affect accounting, such as the diffusion of automation and generative AI tools in finance functions. If such developments drove our results, we would expect a similar shift in accounting labor demand among comparable firms not subject to the mandate.

We therefore re-estimate Equation (1) for firms headquartered in Switzerland, which is a suitable placebo setting for two reasons. First, Swiss firms neither faced nor anticipated mandatory eInvoicing during our sample period. Switzerland has not introduced or announced a B2B eInvoicing mandate, structured eInvoicing is required only of suppliers to the federal administration, and, as a non-EU member, Switzerland is not subject to ViDA. Second, the Swiss economy is closely integrated with Germany's, much of the country shares its language, and Swiss firms are exposed to the same technological and macroeconomic developments.

[Insert Table 7 here]

We construct the Swiss sample using the same procedures as our main sample, including the industry exclusions, LLM-based classification, 16-month window, and March 2024 event date. The final placebo sample comprises 173 firms, 8,304 firm-function-months, and 46,239 job postings. Table 7 presents the results. None of the four coefficients is statistically significant, and the estimates for high-sophistication postings are close to zero. Overall, the placebo test supports the interpretation that the shift toward digitally sophisticated accounting roles in Germany reflects the eInvoicing reform rather than broader trends in the digitalization of accounting work.

## 6 CONCLUSION

This study examines how digitalization affects firms' demand for accounting labor, using the March 2024 passage of Germany's eInvoicing mandate as an externally imposed digitalization shock. We find that the reform does not change the overall level of accounting labor demand but reallocates its composition. Firms become less likely to seek accountants in less digitally sophisticated roles and more likely to seek accountants who can lead and implement digital change. This shift also has a seniority dimension. The decline in low-sophistication postings is concentrated in junior positions, and the increase in high-

sophistication postings occurs in more senior positions, while demand for junior high-sophistication roles declines. The shift appears in permanent rather than temporary positions, indicating that firms seek a lasting change in the digital sophistication of their accounting functions rather than short-term implementation support. Suggestive evidence indicates that the effects are concentrated among firms in less digitally intensive industries, consistent with digitally advanced firms being better prepared to absorb the reform internally. A placebo test using Swiss firms shows no comparable increase in demand for high-sophistication accounting roles.

Taken together, these findings suggest that digitalization acts less as a labor-displacing shock than as a labor-reallocating one: rather than shrinking or expanding the accounting function, the eInvoicing mandate changes whom firms want to hire. This evidence contributes to research on the real effects of accounting and tax regulation by showing that mandated digitalization of tax compliance reshapes the skill composition and seniority structure of accounting labor demand. It also speaks to the broader literature on technological change, supporting the view that digitalization primarily reallocates tasks and reshapes skill demand rather than uniformly displacing labor. For educators and the profession, our results raise the question of how entry-level accountants will acquire the hybrid accounting and digital skills that firms increasingly seek in more senior roles.

Our findings are subject to several limitations. First, job postings capture firms' hiring intentions rather than realized hires. Second, although our design isolates within-firm variation in regulatory exposure and a placebo test shows no comparable shift among Swiss firms, we cannot fully rule out concurrent shocks that affect accounting differently from HR and marketing. Third, our classification of digital sophistication, while validated against human coding, relies on the content of job postings rather than direct observation of the tasks performed once a role is filled. Fourth, our sample consists of firms covered by Compustat

Global, which tend to be larger, and our post-treatment period ends before the first compliance deadline, so we capture firms' preparatory responses rather than long-run effects. Finally, because we study a single reform in a single country, caution is warranted in generalizing the magnitude of our estimates. The underlying mechanism, however, may extend to other settings in which regulation compels firms to digitalize compliance functions. Future research could examine whether similar reallocation follows digital tax reforms in other jurisdictions, how realized hiring and wages respond, and whether the seniority shift we document persists or reverses as digitally sophisticated accounting talent becomes more widely available.

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## APPENDIX A: VARIABLE DEFINITIONS AND PARTITIONS

| Variable Name | Variable Definition |
|---|---|
| **Dependent Variables** | |
| *Postings_Binary* | Indicator variable equal to one if firm *i* posts at least one job in month *t* for function *d*, and zero otherwise. Computed for all postings and separately for postings with low and high digital sophistication. |
| *ihs(Postings_Count)* | Inverse hyperbolic sine of the number of jobs posted by firm *i* in month *t* for function *d*. Computed for all postings and separately for postings with low and high digital sophistication. Measured for firm-months with at least one posting in any of the three functions. |
| **Independent Variables** | |
| *Acct* | Indicator variable equal to one for the accounting function and zero for the HR and marketing functions. |
| *Post* | Indicator variable equal to one for months from March 2024 onward, and zero otherwise. |
| **Digital Sophistication** | |
| Low digital sophistication | Job postings that indicate routine systems use but no digital transformation tasks, as classified by the LLM (Appendix B). |
| High digital sophistication | Job postings that indicate digital transformation tasks, as classified by the LLM (Appendix B). |
| **Sample Partitions** | |
| Junior / Associate- to director-level | Postings with Revelio Labs seniority levels 1–2 (junior) or 3–5 (associate to director). Executive-level postings (levels 6–7) are excluded from the seniority analyses. |
| Temporary / Permanent | Postings classified by the LLM as contract, temporary, internship, or apprenticeship positions (temporary); all other postings, including those without an assigned employment type (permanent). |
| Low / High digital intensity | Firms in industries below / above the sample median of the Eurostat Digital Intensity Index, measured as the share of surveyed German enterprises with high or very high digital intensity in the 2023 survey wave. |

## APPENDIX B: CLASSIFICATION OF DIGITAL SOPHISTICATION

To classify job postings according to the digital sophistication required for a given position, we exploit the capabilities of generative LLMs to read, understand, and interpret text inputs for assessments according to pre-specified frameworks. Specifically, we feed each job posting in our sample into GPT-6-Luna, a large language model. The language model has a May 18, 2026, knowledge cut-off, enabling it to classify both traditional and contemporaneous job descriptions according to their digital sophistication. Our implementation follows the four-step framework proposed by de Kok (2025) for applying generative LLMs in accounting research. Specifically, we (i) define the classification task, (ii) select an appropriate LLM-based classification approach, (iii) develop a structured prompt, and (iv) evaluate construct validity through human validation and robustness analyses. In preparing the prompt, we iteratively refined it through repeated pilot testing on randomly selected job postings before applying it to the full sample.

The objective of our classification task is not merely to identify the presence of digital technologies, but to classify the functional role and sophistication of digital competencies required for the position. Because identical technologies may indicate substantially different competency requirements depending on the surrounding job context, a purely keyword-based approach would not adequately capture the underlying construct. For example, both a basic competency and complex data analysis in Microsoft Excel refer to the same digital tool but with different applications. Accordingly, we select a generative LLM that can incorporate contextual information when assigning digital sophistication categories.

At the beginning of each prompt, we give GPT-6-Luna concise definitions of each category. Specifically, we define five categories of digital sophistication that are hierarchical but not mutually exclusive: Basic Digital Literacy; Routine Systems Use; Data Analytics; Digital Transformation; and Data Engineering. We also define a base category for all job

postings that do not contain sufficient information to support one of the five categories. We allow the model to pick multiple categories if job descriptions indicate different tasks with different digital sophistication requirements, which mitigates concerns about inconsistent classification in edge cases. Our main analyses use two measures derived from these categories: postings with low digital sophistication indicate Routine Systems Use but not Digital Transformation, and postings with high digital sophistication indicate Digital Transformation. We use more granular categories for the classification task to improve its precision, particularly in edge cases where the model might make assumptions about digital sophistication when postings do not clearly map into one of the two groups.

In addition to the digital sophistication categories, we ask the model to indicate whether a job posting is largely noise instead of a proper job posting and what functional area(s) the posting belongs to. We use both outputs to improve the quality of the job postings data. Further, we ask the model to assess each posting's employment type, to indicate whether the position requires leadership tasks, and to list compliance and regulatory challenges mentioned in the posting. Finally, we ask the model to list all phrases that support the digital sophistication assignment. The full prompt is as follows:

*Your task is to analyze a job posting for the digital sophistication it requires. Use the following framework:*

1. *Noise indicator: Assign 1 if the text is noise (e.g., website navigation, login page, session timeout, error page, cookie or privacy notice, or any content that is not an actual job description) rather than a genuine job posting; assign 0 if the text contains a genuine job posting. If 1, the remaining fields may be left at their default or empty values. If the text contains a genuine job posting and only fragments of noisy text, assign 0.*
2. *Functional area: Assign the job posting to one of the following three functional areas: Accounting/Taxation (Acct), HR (HRes), or Marketing (Mrkt). Assign Other (Oth) if the role's primary responsibilities lie outside all three areas. Choose based on the primary responsibilities and tasks described. If the role genuinely spans multiple functional areas with no clear primary, assign all that apply.*
3. *Employment type: Assign the employment type of the role to one of the following: Full-time (FT), Part-time (PT), Contract (CTR), Internship (INT), Apprenticeship (APP), Temporary (TMP), Other (OTH). Choose what best fits the primary employment*

*arrangement described in the job posting. If the job posting does not clearly fit to one employment type, leave the field empty.*

4. *Assess the digital sophistication required for this position (A-F). The categories increase in digital sophistication but are not mutually exclusive; choose all that are explicitly and unambiguously supported by the posting.*
   A. *None: No explicit mention of digital tools, systems, or data-related competencies. Assign only if no other category applies.*
   B. *Basic Digital Literacy: Standard office productivity tools without interaction with enterprise systems; no data analysis beyond formatting or basic tables.*
   C. *Routine Systems Use: Routine transactional use of enterprise platforms (entering, retrieving, or maintaining data within predefined workflows), such as ERP/accounting systems, CRM, HRIS/HCM, applicant tracking systems, marketing automation platforms, or content management systems.*
   D. *Data Analytics: Building, designing, or customizing reports, dashboards, or analyses beyond standard system output; BI tools or structured analytics; no advanced modeling or programming.*
   E. *Digital Transformation: Leading, designing, or implementing digital transformation, system rollouts, process automation, RPA, or enterprise systems configuration.*
   F. *Data Engineering: Programming languages, machine learning, AI, statistical modeling, or cloud data infrastructure applied to the role's tasks.*
5. *Digital evidence: For each selected digital-sophistication level, return the level and the shortest exact phrase from the posting that supports it. Do not list technologies, tools, and competencies that do not support an assigned level. Preserve the wording and language of the posting.*
6. *Leadership indicator (0/1): personnel responsibility, such as managing a team, leading departments, or having direct reports. Assign 0 otherwise. Do not assign 1 based solely on the role's seniority.*
7. *List all compliance and regulatory challenges explicitly mentioned in the posting. Leave empty if none are mentioned.*

*Return only valid JSON matching the schema.*

*Job posting:*
*{job_posting}*

Moreover, to align the model's overall behavior more closely with the domain of the task at hand, we equip it with more general instructions. Instructions allow users to define persistent model behaviors and tune its overall response style and reasoning processes independent of a specific prompt. The full instructions are as follows:

> *You are an expert recruiter responsible for screening and assessing the labor market for corporate jobs using job postings.*

*Job postings are from company career websites or public job boards. They may be in English or the local language.*
*For categorical assessments, return only the applicable category labels without further text.*
*Only consider information explicitly stated in the job posting; do not infer, interpret, or assume information about competencies merely from job titles, hiring firm characteristics, or job seniority. Ignore vague or generic terms unless tied to concrete tasks or tools.*

Consistent with de Kok (2025), we evaluate construct validity of the digital sophistication classification using an independently human-coded benchmark and additional reproducibility analyses. Specifically, we conduct two complementary validation exercises.

First, we validate the algorithmic assignment against a manually coded validation set. We draw a simple random sample of 1,000 job postings from the postings with more than 1,000 characters (Table 1), i.e., before removing noise and postings not assigned to the applicable corporate function. The sample closely mirrors this pool in its composition across corporate functions (393 accounting, 295 HR, and 312 marketing postings), retention status, and highest digital sophistication category. Two of the coauthors independently reviewed each posting together with the LLM's classification and recorded whether it is a genuine job posting, whether it is assigned to the appropriate corporate function, and which digital sophistication categories apply, consistent with the definitions above. A third coauthor reviewed all postings on which the two coders disagreed, as well as postings flagged in additional consistency checks.

The validation mirrors our sample construction in two steps. In the screening step, we compare the LLM's decision to retain a posting (a genuine job posting, assigned to the applicable corporate function) with the human assessment. The LLM agrees with the final human assessment in 98.0% of cases (Cohen's $\kappa = 0.934$). Of the 1,000 postings, the coders consider 823 relevant (4 are noise and 173 are not in the applicable function), whereas the LLM retains 807. Of these 807 postings, 805 (99.8%) are confirmed as relevant, so our final sample

is virtually free of noise and misassigned postings. Conversely, the LLM excludes only 18 of the 823 relevant postings (2.2%; 13 as not in the applicable function and 5 without any digital sophistication category).

In the classification step, we compare the highest digital sophistication category on the 805 postings retained by both the LLM and the coders. We find an overall accuracy of 91.3% (97.8% within one category) and a quadratic-weighted Cohen's $\kappa$ of 0.936. Precision ranges between 79.8% (Basic Digital Literacy) and 98.1% (Digital Transformation), and recall between 87.0% (Routine Systems Use) and 95.0% (Basic Digital Literacy); the unweighted averages of precision and recall are both 91.6%. Accuracy (quadratic-weighted Cohen's $\kappa$) is 91.6% (0.926) for accounting, 93.0% (0.975) for HR, and 88.8% (0.894) for marketing postings. Appendix Table B-1 reports the details on precision and recall, and Appendix Figure B-1 presents the results in the form of a confusion matrix. Overall, we conclude that misclassifications are low and concentrated in adjacent categories.

Second, we assess the reproducibility of the LLM-based classification by repeating the classification of the same 1,000 job postings 100 times with identical prompts and model settings, yielding a total of 100,000 LLM-based assignments. In the screening step, the retention decision is highly consistent across runs (Fleiss' $\kappa = 0.865$). For the 805 postings in the classification step, the highest digital sophistication category is likewise consistent across runs (Fleiss' $\kappa = 0.823$). Importantly, the validity of the classification does not hinge on the particular run we use in our analysis: scored against the validation set, the accuracy of the 100 runs averages 90.4% (ranging from 88.4% to 94.0%), compared with 91.3% for the classification used in our analysis (Appendix Figure B-2). Jointly, these results indicate that the LLM-based assignment performs in a reliable, replicable, and internally consistent manner.

To further describe how the digital sophistication categories differ in substance, we exploit the "digital evidence" field the LLM returns, which contains the shortest verbatim

phrases from a posting that support the respective categorization. We pool these evidence phrases across all sample postings (except "None" as it carries no evidence) and identify, for each category, the terms that are most distinctive relative to the other categories. For every term, we compare how often it appears among the phrases of one category with how often it appears among the phrases of all other categories, and score the term by how much more (or less) typical it is for that category. Formally, the score is the log-odds ratio of the term's frequency in one category versus all other categories (Monroe et al., 2008). We scale the score by its statistical uncertainty (its standard error, yielding a *z*-score), so a term needs to be both clearly more common in a category and used often enough to be reliable. We additionally shrink each term's frequency toward its overall frequency using an informative Dirichlet prior, which prevents very rare terms from receiving extreme scores. As a result, terms that appear in every category are not highlighted, and terms that are used only a handful of times are not either. Appendix Figure B-3 shows the fifteen highest-scoring terms for each digital sophistication category.

**APPENDIX TABLE B-1 Accuracy of LLM Classification of Digital Sophistication**

| *Panel A: Overall* | Precision | | Recall | |
|---|---|---|---|---|
| | Score | N | Score | N |
| None | 0.963 | 81 | 0.918 | 85 |
| Basic Digital Literacy | 0.798 | 119 | 0.950 | 100 |
| Routine Systems Use | 0.913 | 206 | 0.870 | 216 |
| Data Analytics | 0.921 | 280 | 0.935 | 276 |
| Digital Transformation | 0.981 | 107 | 0.905 | 116 |
| Data Engineering | 0.917 | 12 | 0.917 | 12 |

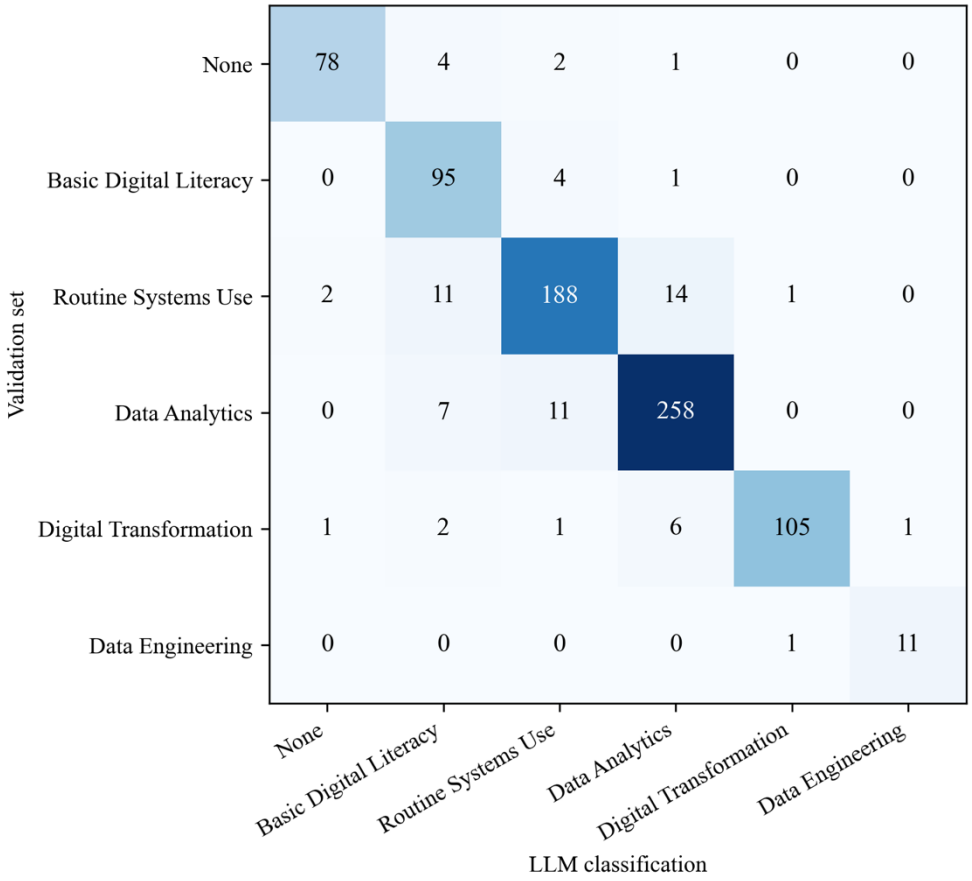
| *Panel B: Accounting* | Precision | | Recall | |
|---|---|---|---|---|
| | Score | N | Score | N |
| None | 0.950 | 20 | 0.950 | 20 |
| Basic Digital Literacy | 0.815 | 27 | 0.957 | 23 |
| Routine Systems Use | 0.926 | 95 | 0.889 | 99 |
| Data Analytics | 0.903 | 113 | 0.936 | 109 |
| Digital Transformation | 0.969 | 64 | 0.912 | 68 |
| Data Engineering | 0.750 | 4 | 0.750 | 4 |

| *Panel C: HR* | Precision | | Recall | |
|---|---|---|---|---|
| | Score | N | Score | N |
| None | 1.000 | 32 | 0.914 | 35 |
| Basic Digital Literacy | 0.857 | 42 | 0.947 | 38 |
| Routine Systems Use | 0.915 | 71 | 0.915 | 71 |
| Data Analytics | 0.920 | 75 | 0.932 | 74 |
| Digital Transformation | 1.000 | 34 | 0.944 | 36 |
| Data Engineering | 1.000 | 4 | 1.000 | 4 |

| *Panel D: Marketing* | Precision | | Recall | |
|---|---|---|---|---|
| | Score | N | Score | N |
| None | 0.931 | 29 | 0.900 | 30 |
| Basic Digital Literacy | 0.740 | 50 | 0.949 | 39 |
| Routine Systems Use | 0.875 | 40 | 0.761 | 46 |
| Data Analytics | 0.946 | 92 | 0.935 | 93 |
| Digital Transformation | 1.000 | 9 | 0.750 | 12 |
| Data Engineering | 1.000 | 4 | 1.000 | 4 |

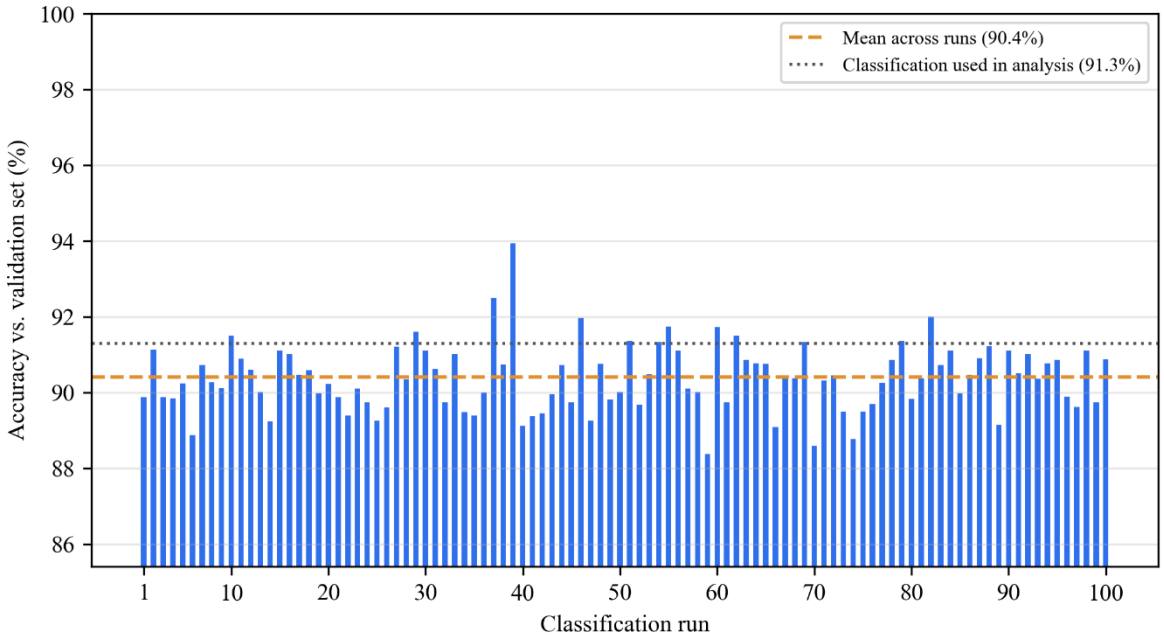
Notes: This table presents metrics to assess the quality of LLM-based digital sophistication category assignment using GPT-6-Luna. To evaluate model fit, we manually assign 1,000 job postings as described in Appendix B and compare the LLM's assignments against this validation set for the 805 postings retained by both the LLM and the coders. Specifically, we assess the precision and recall of GPT-6-Luna in correctly identifying the highest digital sophistication category of a job posting, both in aggregate (Panel A) and by corporate function (Panels B-D). Precision measures the proportion of job postings that the model assigns to a given digital sophistication category (true positives and false positives) that are correctly assigned to that category (true positives). Recall measures the proportion of job postings that truly belong to a given digital sophistication category (true positives + false negatives) that the model correctly assigns to that category (true positives). We report both the score and the underlying sample size for each digital sophistication category.

## APPENDIX FIGURE B-1 Confusion Matrix



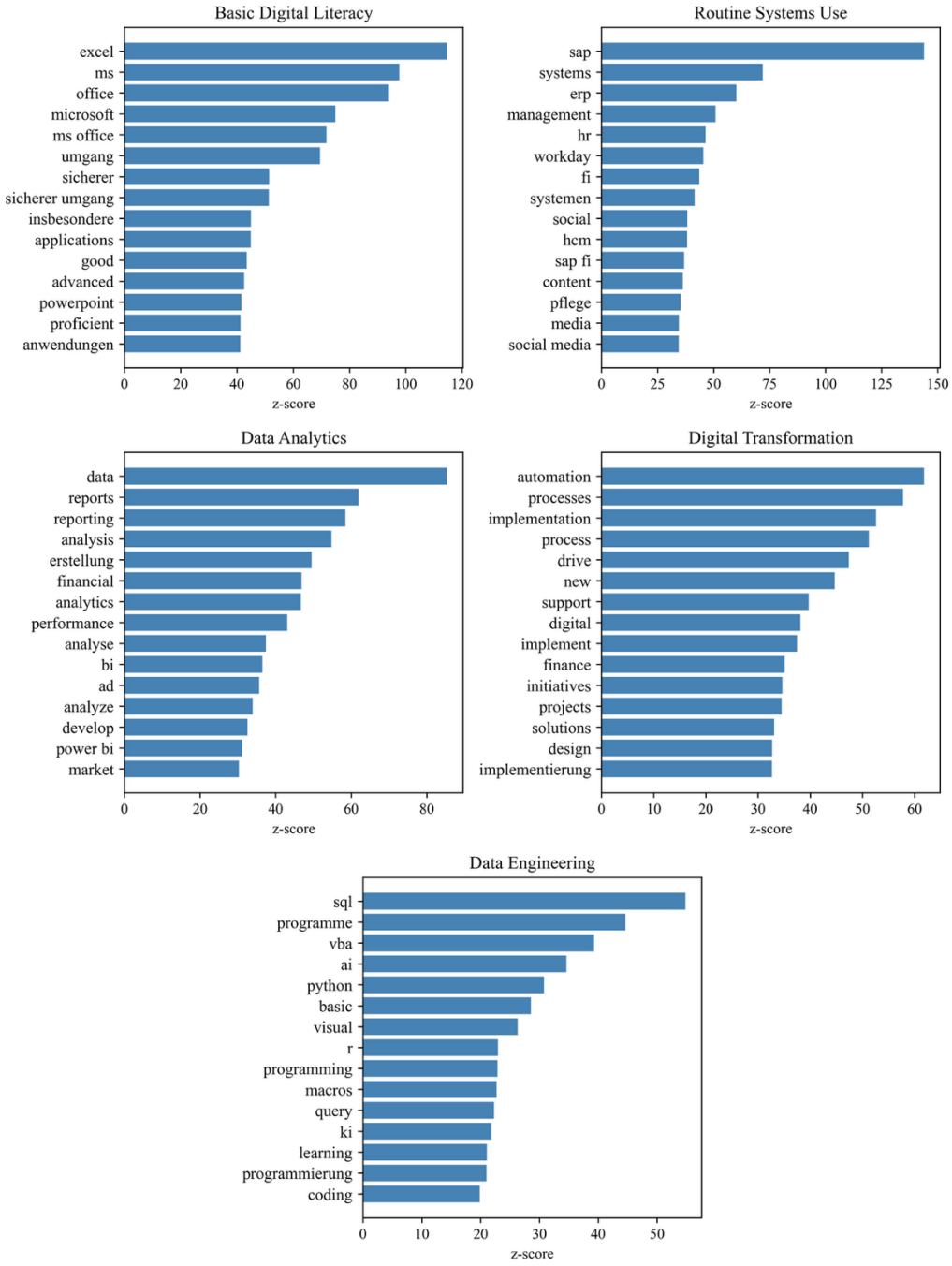

Notes: This figure presents the confusion matrix of the highest digital sophistication category for the 805 validation postings retained by both the LLM and the human coders. Rows report the category in the validation set, columns the category assigned by the LLM; diagonal cells are correct assignments.

## APPENDIX FIGURE B-2 Accuracy of Repeated LLM Classifications




Notes: This figure presents the accuracy of repeated LLM-based classifications of digital sophistication using GPT-6-Luna. To evaluate whether the validity of the classification depends on the particular classification run used in our analysis, we classify the 805 validation postings retained by both the LLM and the human coders 100 times, using identical prompts and model settings. For each run, the bars report the share of postings whose highest digital sophistication category matches the validation set. The dashed line marks the mean accuracy across all 100 runs. The dotted line marks the accuracy of the classification used in our analysis.

## APPENDIX FIGURE B-3 Distinctive Terms by Digital Sophistication Category




Notes: This figure presents the most distinctive terms per digital sophistication category, based on the verbatim evidence phrases returned by the LLM. For each job posting, the model returns the shortest phrase from the posting that supports each assigned category. We pool these phrases across all sample postings and assign each phrase to the category it supports; phrases that cannot be attributed to a single category are excluded. We split the phrases into single words and two-word combinations, remove common stop words in English and German, and retain terms that appear in at least 15 phrases. For each term and category, we compare the frequency of the term among the phrases of that category with its frequency among the phrases of all other categories, and compute the log-odds ratio of the two. We use an informative Dirichlet prior based on the overall term frequencies, which shrinks the scores of rarely used terms toward zero, and divide the log-odds ratio by its standard error. Each panel plots the fifteen terms with the highest resulting score ($z$-score) for the respective category on the horizontal axis. Higher values indicate that a term is used more frequently, and more reliably so, in the evidence phrases of that category than in those of the other categories.

## APPENDIX C: EXAMPLE JOB POSTINGS

This appendix provides excerpts from two job postings in the sample, one with low and one with high digital sophistication. Bold text marks the phrases the LLM returned as evidence for its classification (Appendix B). Excerpts are shortened, translated from German where indicated, and lightly reformatted for readability.

**Firm: Continental AG**
**Job Title: Financial Accountant (m/f/d)**
**Digital Sophistication Classification: Low**
**Job Description (excerpt):**

[…]
Job Description

- Smooth execution of day-to-day accounting operations
- Ensure complete and timely recording of accounting transactions
- **Submit required reports (FRT, IDEV) on time**
- Optimize accounting processes
- Accounting
  - Collect, organize, and file accounting documents
  - Verify documents for completeness and formal accuracy
  - Create and maintain master data (debtors and creditors)
  - Process incoming payment reminders
  - **Maintain statistics (internal/external), including weekly FRT reports and monthly IDEV reports**
- Accounts Payable / Accounts Receivable
  - Manage the petty cash fund, including accounting entries
  - Pre-record and post incoming invoices
  - Process travel expense claims and employee reimbursements
  - Prepare the weekly payment run
  - Post bank statements, including credit card statements
  - Upload customer invoices
  - Prepare due date reports and support credit management
  - Monitor incoming payments and prepare and send payment reminders (collections process)

Qualifications

- Completed vocational training/apprenticeship as an Industrial Clerk, Office Management Clerk, Tax Clerk, or a comparable qualification
- Several years of experience in the areas listed above
- **Proficiency in** Microsoft Office applications (Excel, Word, and Outlook), **kekwin, and SAP**
- Business-fluent German and very good written and spoken English skills
- Willingness to participate in continuous professional development and training
- Class B driver's license

Applications from severely disabled individuals are welcome.
[…] *[Note: Translated from German, structurally improved for readability]*

**Firm: KWS SAAT SE & Co. KGaA**
**Job Title: Functional Automation Lead Finance (m/f/d)**
**Digital Sophistication Classification: High**
**Job Description (excerpt):**

Are you passionate about **making people's work lives easier through automation and new technologies**? Got that can-do attitude, love shaking things up, and possess the analytical skills to spot opportunities and the structure to make them happen? Well, guess what? KWS Berlin GmbH is looking for a full-time, permanent Functional Automation Lead Finance (m/f/d) for our Berlin office. We need someone who's not afraid to challenge the status-quo, dive deep into Finance processes, mainly General Ledger, indirect Tax or Treasury, and proactively drive our automation initiatives. If you're a strategic thinker who loves **optimizing processes, implementing automation solutions**, and collaborating with awesome teams, then we want to hear from you!

Make an impact:

- Create a **comprehensive automation strategy** and roadmap aligned with the functional strategy goals and overall business objectives
- **Proactively identify opportunities for process improvement and efficiency gains through automation**, optimizing the entire value chain, including screening the market for relevant technologies
- **Lead the implementation of automation solutions**, ensuring seamless integration with existing systems and compliance with IT and automation governance
- **Work closely with process owners, stakeholders, and central functions such as Global IT, Expert Hub, the Automation and Data Analytics Team and external partners to drive end-to-end automation solutions**
- Offer training and support to colleagues on automation tools and methodologies, fostering a culture of learning and knowledge sharing
- Implement **monitoring mechanisms to track the performance of automated processes and generate regular reports on the impact of automation**, including efficiency gains and cost savings

Bring your strength:

- Bachelor's or master's degree in Business Administration, Data Science, IT, or a related field
- Demonstrated **experience in leading and driving automation initiatives**, preferably within a Shared Service Center environment
- Strong understanding of Finance processes and workflows, with proficiency in systems such as SAP R3 and S/4
- **Proficiency in automation tools** (e.g., MS Power Platform) and advanced skills in data visualization tools (e.g., Tableau, Power BI, etc.)
- Willingness to learn and adapt to new technologies and methodologies

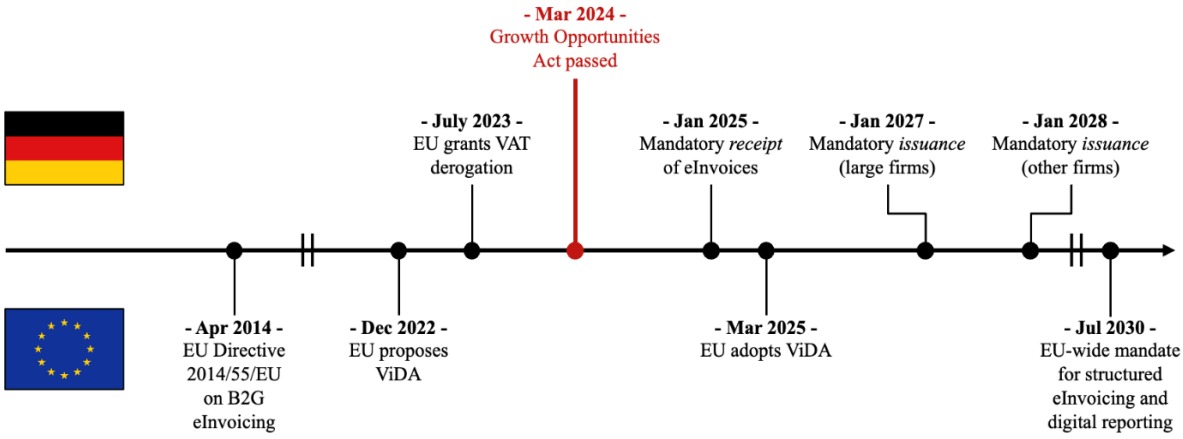
[…]

*[Note: Structurally improved for readability]*

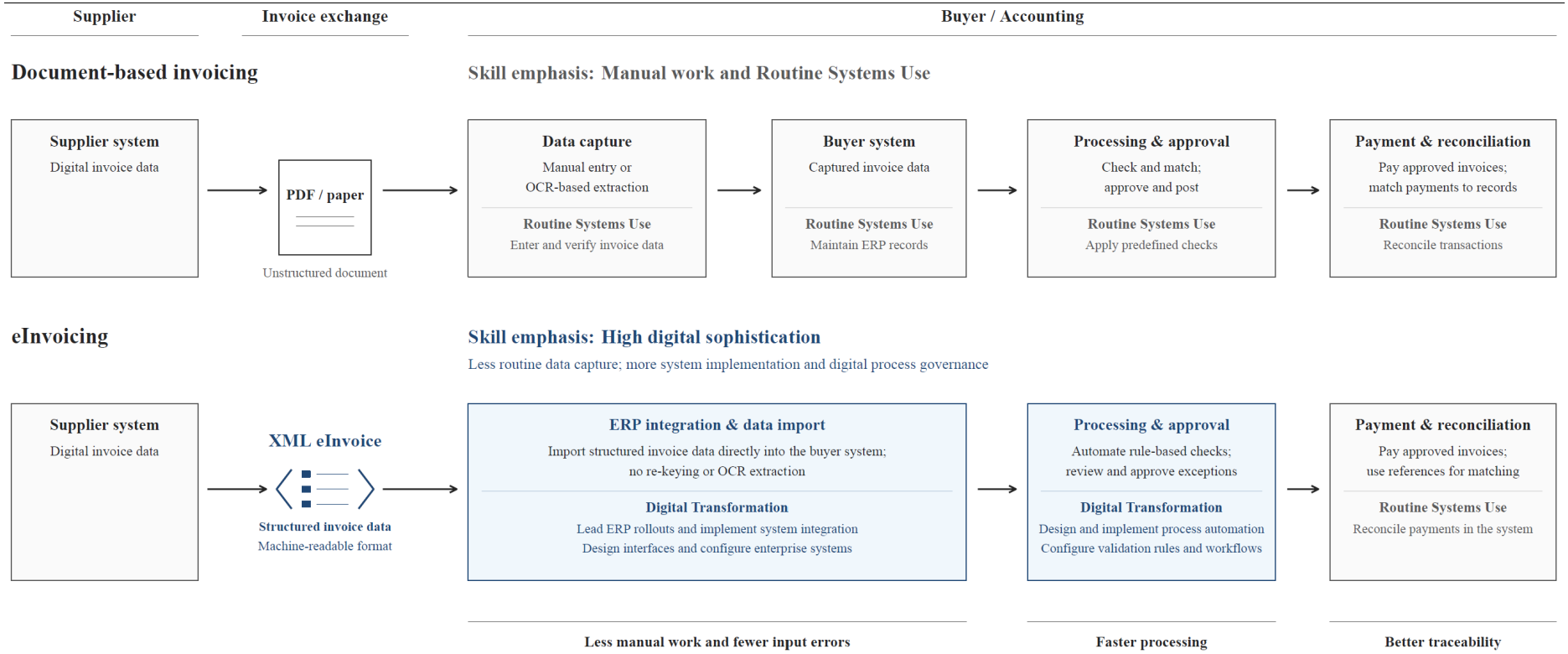
## FIGURES AND TABLES

### FIGURE 1 Institutional Background

*Panel A: Timeline of eInvoicing Regulation in Germany and Europe*

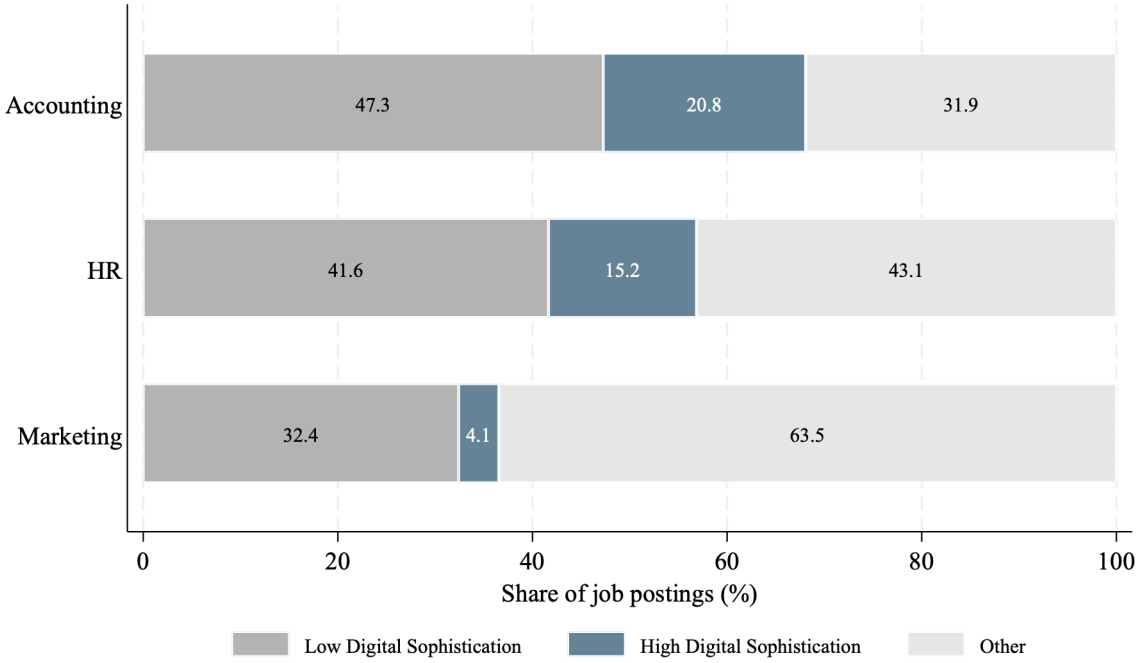


*Panel B: Traditional versus Electronic Invoicing Processes*




Notes: Panel A visualizes the timeline of the passage of mandatory B2B eInvoicing in Germany and the European Union. It highlights key regulatory milestones, including the adoption of Directive 2014/55/EU, the proposal and adoption of the ViDA initiative, and the phased implementation of mandatory structured eInvoicing in Germany. March 2024 marks the passage of the Growth Opportunities Act, which mandates firms to be able to receive structured eInvoices for B2B transactions from January 2025 onwards, with subsequent obligations regarding the issuance of eInvoices scheduled for later stages. Panel B contrasts traditional document-based invoicing with structured eInvoicing and illustrates how skill requirements shift from manual processing and routine systems use toward system implementation, configuration, and process automation. The workflows are illustrative; benefits depend on system integration, and automation may also exist in document-based workflows. eInvoicing does not itself initiate payment. ERP denotes enterprise resource planning; OCR denotes optical character recognition; XML denotes Extensible Markup Language, a format for encoding structured, machine-readable invoice data.

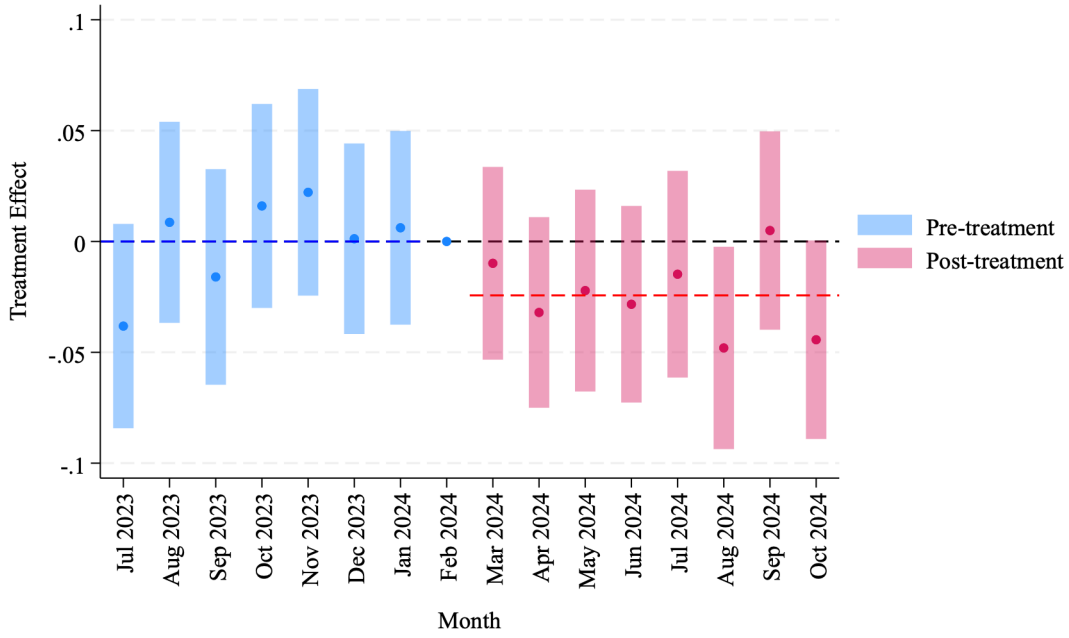
**FIGURE 2 Distribution of Digital Sophistication by Function**



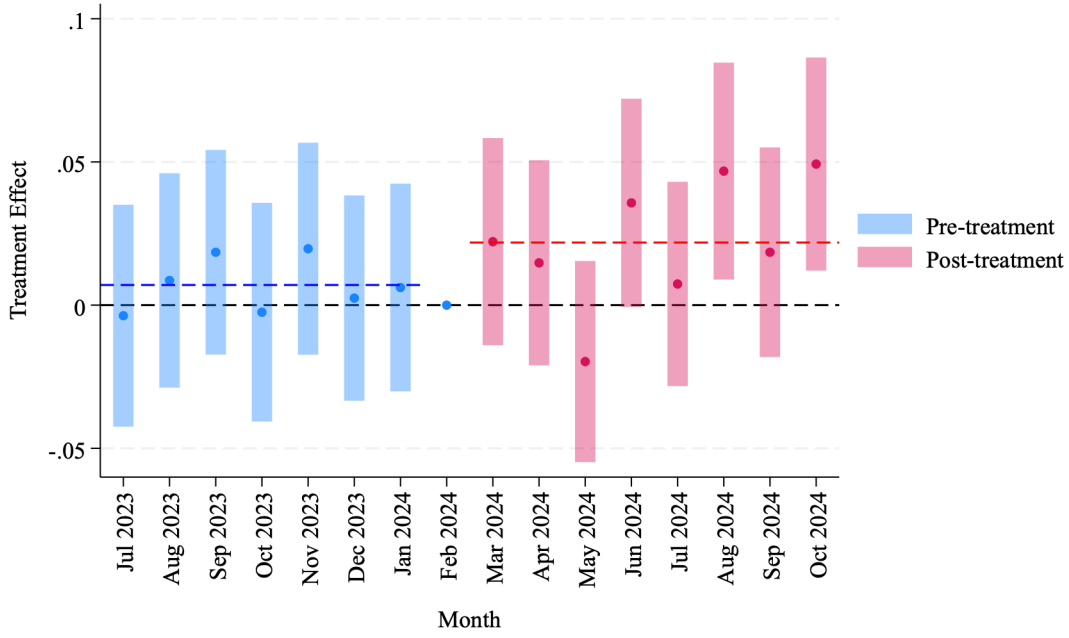

Notes: This figure presents a stacked horizontal bar chart that visualizes the distribution of digital sophistication levels separately for each corporate function included in the sample (accounting, HR, marketing) at the job posting level. The dark grey area refers to job postings with low digital sophistication, the blue area refers to job postings with high digital sophistication, and the light grey area refers to all other job postings not captured by our definition of digital sophistication.

**FIGURE 3 Treatment Dynamics**

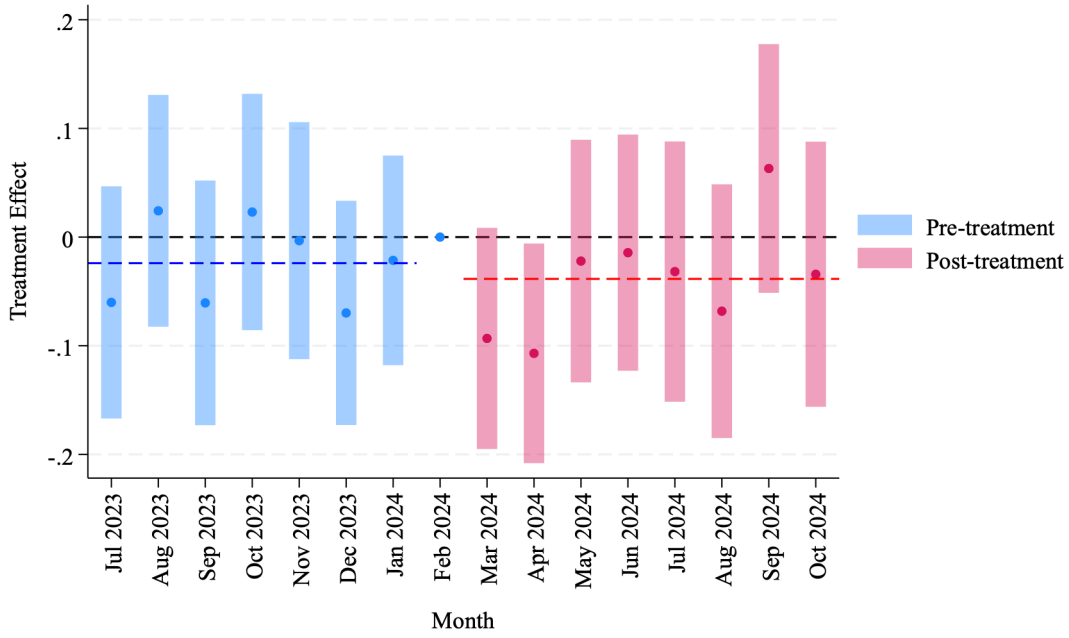
Panel A: *Postings_Binary* (Low Digital Sophistication)



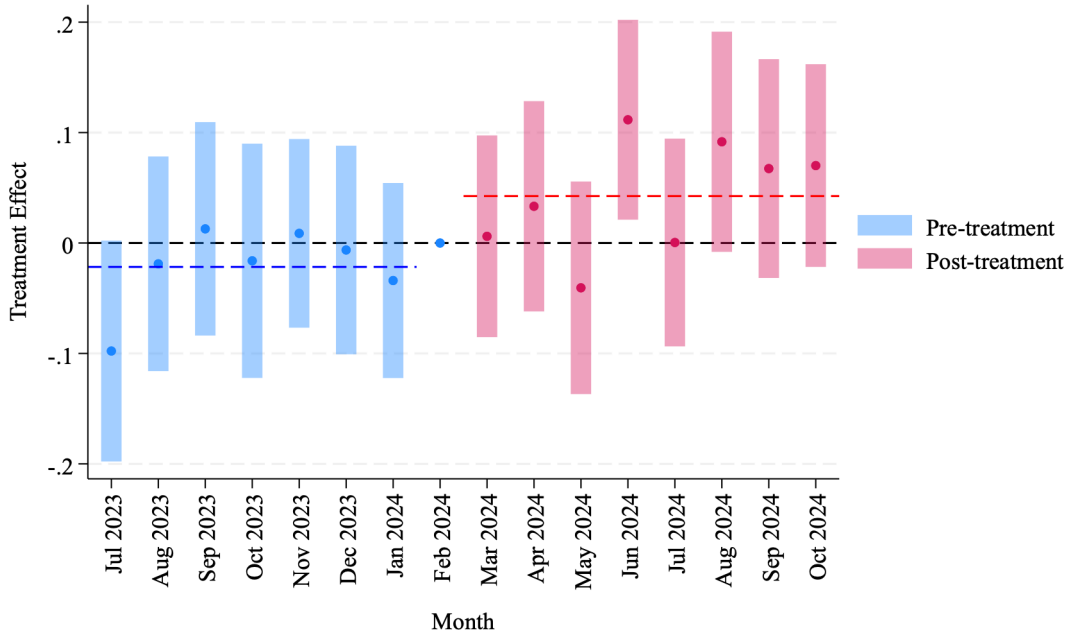

Panel B: *Postings_Binary* (High Digital Sophistication)



Panel C: *ihs(Postings_Count)* (Low Digital Sophistication)

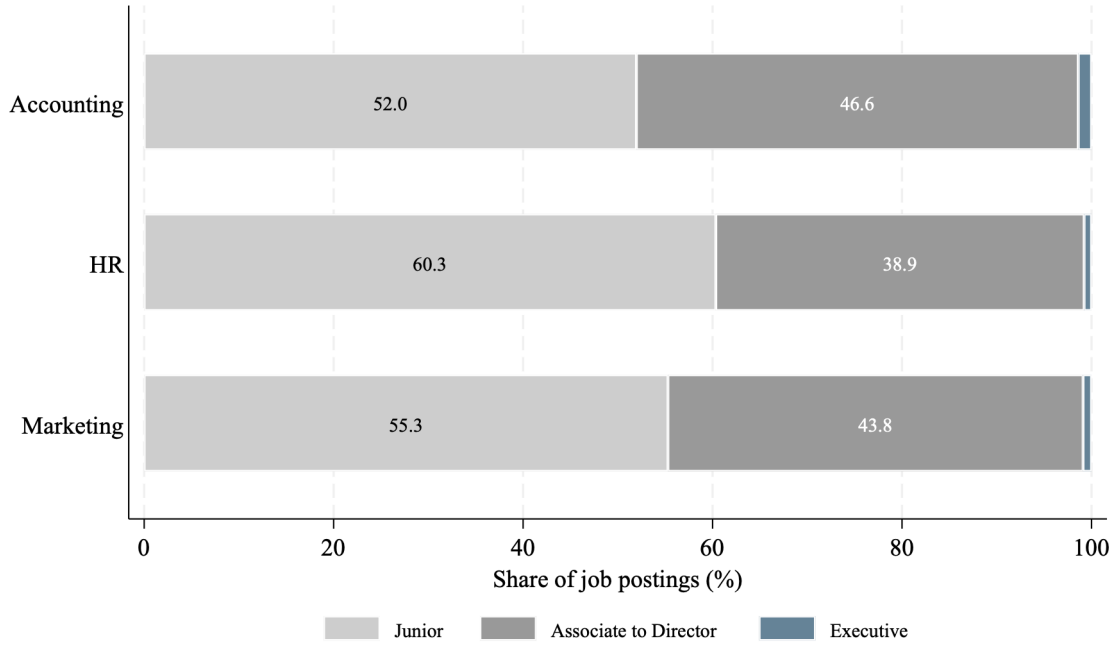



Panel D: *ihs(Postings_Count)* (High Digital Sophistication)



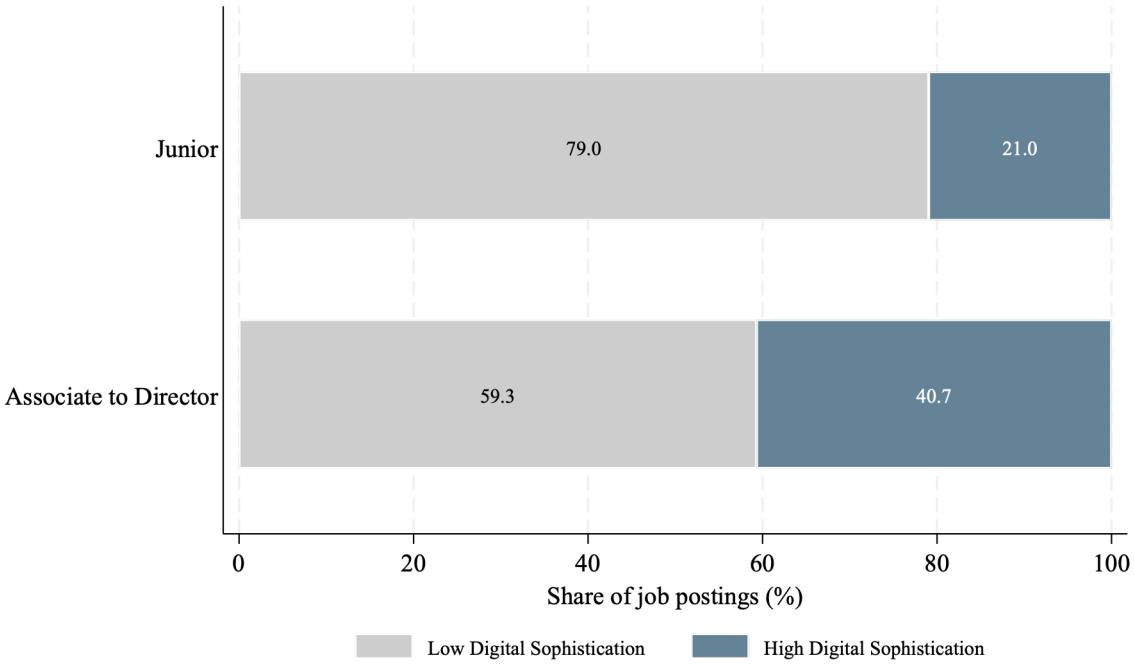

Notes: This figure visualizes treatment dynamics before and after the passage of mandatory eInvoicing in Germany. We re-estimate the difference-in-differences specification reported in Equation (1), using *Postings_Binary* as dependent variable in Panels A and B, and *ihs(Postings_Count)* in Panels C and D. We replace the difference-in-differences estimator with month-specific indicator variables interacted with *Acct*, using February 2024 as the baseline month. Panels A and C consider job postings that require labor with low digital sophistication, whereas Panels B and D consider job postings that require labor with high digital sophistication. The figure presents coefficient estimates for each monthly interaction term, along with 90% confidence intervals as vertical bars. The horizontal dashed lines reflect the mean coefficient magnitude in the respective period. All specifications employ linear OLS regressions and include firm-month- and function-fixed effects. Standard errors are clustered by firm-function. Continuous variables are winsorized at the 1st and 99th percentiles.

**FIGURE 4 Distribution of Seniority Levels by Function**



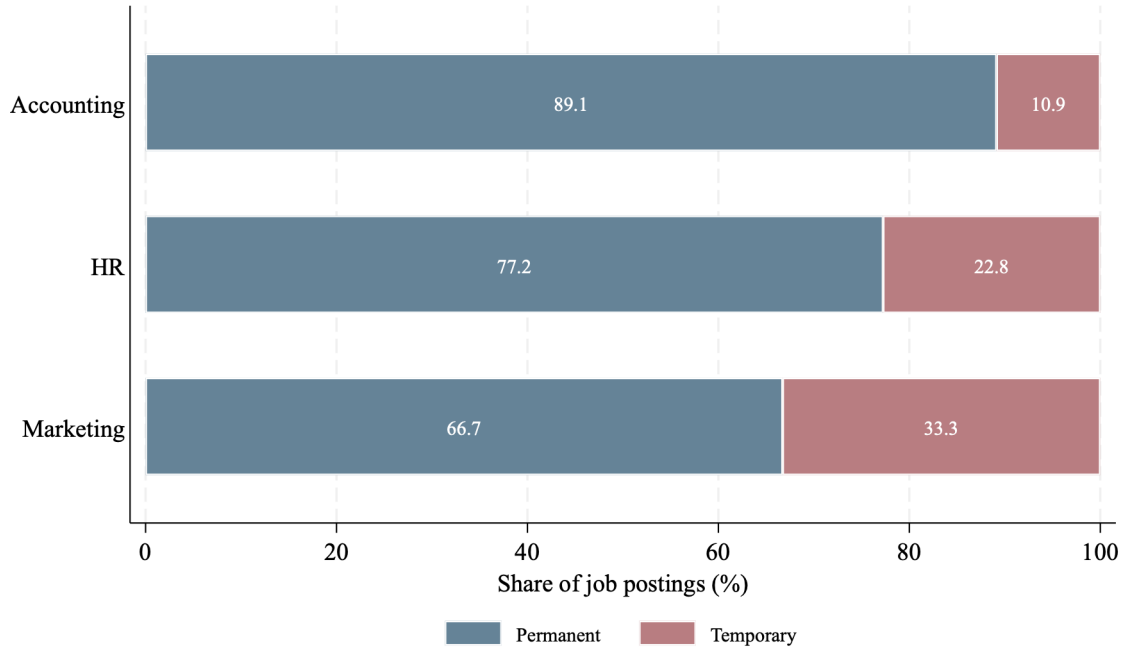

Notes: This figure presents a stacked horizontal bar chart that visualizes the distribution of seniority levels separately for each corporate function included in the sample (accounting, HR, marketing) at the job posting level. The light grey area refers to junior-level job postings, the dark grey area refers to associate- to director-level job postings, and the blue area refers to executive-level job postings.

**FIGURE 5 Distribution of Accountants' Seniority Levels by Digital Sophistication**




Notes: This figure presents a stacked horizontal bar chart that visualizes the distribution of low versus high digital sophistication levels in accounting functions by seniority group. The light grey area refers to job postings indicating low digital sophistication and the blue area refers to job postings indicating high digital sophistication.

**FIGURE 6 Distribution of Employment Types by Function**




Notes: This figure presents a stacked horizontal bar chart that visualizes the distribution of employment types separately for each corporate function included in the sample (accounting, HR, marketing) at the job posting level. The blue area refers to permanent positions (listed as full-time, part-time, unspecified, or "other"), and the red area refers to temporary positions (listed as temporary, contract, internship or apprenticeship). Postings without a stated employment type are classified as permanent.

**TABLE 1 Sample Selection**

| | Requirement | # Firms | # Postings | # Firm-Function-Months |
|---|---|---|---|---|
| | Firms headquartered in Germany with data availability in Compustat Global and Revelio Labs | 687 | | |
| – | Firms in Employment Services (NAICS 5613); or Accounting, Tax Preparation, Bookkeeping, and Payroll Services (NAICS 5412) | 686 | | |
| – | Firms with business description suggesting product market response to digital compliance reform that are assigned to Software Publishers (NAICS 5112/5132); Data Processing, Hosting, and Related Services (NAICS 5182); or Computer Systems Design and Related Services (NAICS 5415) | 655 | | |
| – | Firms without accounting/tax, HR, or marketing job postings during sample period | 423 | 146,480 | 20,304 |
| – | Job postings with no more than 1,000 characters | 415 | 129,503 | 19,920 |
| – | Job postings assigned as noise, not assigned to appropriate function, or where the model did not return any digital sophistication category | 406 | 101,847 | 19,488 |
| = | **Final Sample** | **406** | **101,847** | **19,488** |

Notes: This table summarizes the sample selection procedure. We obtain raw job postings data from Revelio Labs and financial data from Compustat Global. The sample includes job postings for positions in accounting and taxation, HR, and marketing by firms headquartered in Germany during the 16-month window from July 2023 through October 2024. We identify noise, assign postings to corporate functions, and classify their digital sophistication using the LLM-based procedure described in Appendix B. We aggregate postings to the firm-function-month level and set posting activity to zero in firm-function-months without observed postings, yielding 19,488 observations (406 firms × 3 functions × 16 months).

**TABLE 2 Descriptive Statistics**

*Panel A: Sample Composition by Corporate Function and Time*

| | Accounting | HR | Marketing | Total |
|---|---|---|---|---|
| Post = 0 | 3,248 | 3,248 | 3,248 | 9,744 |
| Post = 1 | 3,248 | 3,248 | 3,248 | 9,744 |
| Total | 6,496 | 6,496 | 6,496 | 19,488 |

*Panel B: Sample Composition by Industry*

| | Industry (Two-Digit NAICS) | Firms | Percent |
|---|---|---|---|
| 11 | Agriculture, Forestry, Fishing and Hunting | 1 | 0.25 |
| 21 | Mining | 1 | 0.25 |
| 22 | Utilities | 17 | 4.19 |
| 23 | Construction | 10 | 2.46 |
| 31-33 | Manufacturing | 185 | 45.57 |
| 42 | Wholesale Trade | 7 | 1.72 |
| 44-45 | Retail Trade | 19 | 4.68 |
| 48-49 | Transportation and Warehousing | 11 | 2.71 |
| 51 | Information | 35 | 8.62 |
| 52 | Finance and Insurance | 54 | 13.30 |
| 53 | Real Estate Rental and Leasing | 20 | 4.93 |
| 54 | Professional, Scientific, and Technical Services | 21 | 5.17 |
| 56 | Administrative, Support, Waste Management, Remediation Serv. | 4 | 0.99 |
| 61 | Educational Services | 1 | 0.25 |
| 62 | Health Care and Social Assistance | 7 | 1.72 |
| 71 | Arts, Entertainment, and Recreation | 7 | 1.72 |
| 72 | Accommodation and Food Services | 2 | 0.49 |
| 81 | Other Services (except Public Administration) | 1 | 0.25 |
| 99 | Non-classifiable Establishments | 3 | 0.74 |
| | | 406 | 100 |

*Panel C: Summary Statistics*

| | N | Mean | SD | P25 | P50 | P75 |
|---|---|---|---|---|---|---|
| *Acct* | 19,488 | 0.333 | 0.471 | 0 | 0 | 1 |
| *Post* | 19,488 | 0.500 | 0.500 | 0 | 0.5 | 1 |
| | | | | | | |
| *Postings_Binary* | 19,488 | 0.409 | 0.492 | 0 | 0 | 1 |
| *[Low Dig. Sophistication]* | 19,488 | 0.307 | 0.461 | 0 | 0 | 1 |
| *[High Dig. Sophistication]* | 19,488 | 0.154 | 0.361 | 0 | 0 | 0 |
| *(Accounting only)* | 6,496 | 0.485 | 0.500 | 0 | 0 | 1 |
| *(HR only)* | 6,496 | 0.382 | 0.486 | 0 | 0 | 1 |
| *(Marketing only)* | 6,496 | 0.358 | 0.480 | 0 | 0 | 1 |
| | | | | | | |
| *Postings_Count* | 11,907 | 7.596 | 16.513 | 0.000 | 1.000 | 6.000 |
| *[Low Dig. Sophistication]* | 11,907 | 3.186 | 7.068 | 0.000 | 1.000 | 2.000 |
| *[High Dig. Sophistication]* | 11,907 | 0.920 | 2.488 | 0.000 | 0.000 | 1.000 |
| *(Accounting only)* | 3,969 | 9.586 | 19.656 | 1.000 | 2.000 | 8.000 |
| *(HR only)* | 3,969 | 6.987 | 14.882 | 0.000 | 1.000 | 6.000 |
| *(Marketing only)* | 3,969 | 6.198 | 14.481 | 0.000 | 1.000 | 4.000 |
| | | | | | | |
| *ihs(Postings_Count)* | 11,907 | 1.489 | 1.470 | 0.000 | 0.881 | 2.492 |
| *[Low Dig. Sophistication]* | 11,907 | 0.966 | 1.214 | 0.000 | 0.881 | 1.444 |
| *[High Dig. Sophistication]* | 11,907 | 0.415 | 0.823 | 0.000 | 0.000 | 0.881 |
| *(Accounting only)* | 3,969 | 1.783 | 1.457 | 0.881 | 1.444 | 2.776 |
| *(HR only)* | 3,969 | 1.418 | 1.473 | 0.000 | 0.881 | 2.492 |
| *(Marketing only)* | 3,969 | 1.266 | 1.431 | 0.000 | 0.881 | 2.095 |

Notes: This table provides descriptive statistics. Panel A describes the number of firm-function-months by corporate function (accounting, HR, and marketing) for the eight pre-treatment and eight post-treatment months. Panel B reports the distribution of sample firms by two-digit NAICS industry. Panel C reports summary statistics for the main variables, both for all postings and separately by digital sophistication level. Low digital sophistication refers to job postings that indicate routine systems use but no digital transformation tasks; high digital sophistication refers to postings that indicate digital transformation tasks. *Postings_Binary* is measured over all firm-function-months. *Postings_Count* and *ihs(Postings_Count)* are measured over firm-months with at least one posting in any of the three functions (3,969 firm-months × 3 functions = 11,907 observations). Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in Appendix A.

**TABLE 3 Demand for Digital Sophistication in Accounting-Related Labor**

| DV = | *Postings_Binary* | | | *ihs(Postings_Count)* | | |
|---|---|---|---|---|---|---|
| | All Postings | By Digital Sophistication | | All Postings | By Digital Sophistication | |
| | | Low Dig. Sophis-tication | High Dig. Sophis-tication | | Low Dig. Sophis-tication | High Dig. Sophis-tication |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Acct* × *Post*** | **-0.0115** | **-0.0243**** | **0.0157*** | **0.0488** | **-0.0193** | **0.0612**** |
| | **(-0.903)** | **(-1.995)** | **(1.682)** | **(1.365)** | **(-0.581)** | **(2.394)** |
| Firm × Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Function FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE | Firm × Function | Firm × Function | Firm × Function | Firm × Function | Firm × Function | Firm × Function |
| Adjusted $R^2$ | 0.4973 | 0.4758 | 0.3966 | 0.7121 | 0.6532 | 0.4815 |
| N | 19,488 | 19,488 | 19,488 | 11,907 | 11,907 | 11,907 |

Notes: This table provides results from estimating the difference-in-differences specification reported in Equation (1), using *Postings_Binary* as dependent variable in Columns (1)-(3) and *ihs(Postings_Count)* in Columns (4)-(6). The dependent variables used in Columns (1) and (4) consider all job postings within a given firm-function-month when constructing the respective dependent variable. The dependent variables used in Columns (2) and (5) consider job postings that require labor with low digital sophistication, whereas those in Columns (3) and (6) consider job postings that require labor with high digital sophistication. All specifications employ linear OLS regressions and include firm-month- and function-fixed effects. We present t-statistics in parentheses. Standard errors are clustered by firm-function. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% level, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in Appendix A.

**TABLE 4 Accounting Labor Demand by Seniority**

*Panel A: Junior-Level Positions*

| DV = | *Postings_Binary* | | *ihs(Postings_Count)* | |
|---|---|---|---|---|
| | Low Dig. Sophis-tication (1) | High Dig. Sophis-tication (2) | Low Dig. Sophis-tication (3) | High Dig. Sophis-tication (4) |
| ***Acct × Post*** | **-0.0240**** | **-0.0183**** | **-0.0374** | **-0.0365*** |
| | **(-2.137)** | **(-2.327)** | **(-1.319)** | **(-1.826)** |
| Firm × Month FE | Yes | Yes | Yes | Yes |
| Function FE | Yes | Yes | Yes | Yes |
| Clustered SE | Firm × Function | Firm × Function | Firm × Function | Firm × Function |
| Adjusted $R^2$ | 0.4681 | 0.3298 | 0.6320 | 0.3812 |
| N | 19,488 | 19,488 | 11,907 | 11,907 |

*Panel B: Associate- to Director-Level Positions*

| DV = | *Postings_Binary* | | *ihs(Postings_Count)* | |
|---|---|---|---|---|
| | Low Dig. Sophis-tication (1) | High Dig. Sophis-tication (2) | Low Dig. Sophis-tication (3) | High Dig. Sophis-tication (4) |
| ***Acct × Post*** | **-0.0032** | **0.0320***** | **0.0209** | **0.0838***** |
| | **(-0.297)** | **(3.635)** | **(0.691)** | **(3.599)** |
| Firm × Month FE | Yes | Yes | Yes | Yes |
| Function FE | Yes | Yes | Yes | Yes |
| Clustered SE | Firm × Function | Firm × Function | Firm × Function | Firm × Function |
| Adjusted $R^2$ | 0.4165 | 0.3453 | 0.5350 | 0.4089 |
| N | 19,488 | 19,488 | 11,907 | 11,907 |

Notes: This table provides results from estimating the difference-in-differences specification reported in Equation (1). The dependent variables in Panel A include only job postings for junior-level positions, whereas those in Panel B include only job postings for associate- to director-level positions. Columns (1) and (2) of either panel use *Postings_Binary* as the dependent variable; Columns (3) and (4) of either panel use *ihs(Postings_Count)* as the dependent variable. The dependent variables used in Columns (1) and (3) of each panel consider job postings that require labor with low digital sophistication, whereas those in Columns (2) and (4) consider job postings that require labor with high digital sophistication. All specifications employ linear OLS regressions and include firm-month- and function-fixed effects. We present t-statistics in parentheses. Standard errors are clustered by firm-function. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% level, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in Appendix A.

**TABLE 5 Accounting Labor Demand by Employment Type**

*Panel A: Demand for Temporary Positions*

| DV = | *Postings_Binary* | | *ihs(Postings_Count)* | |
|---|---|---|---|---|
| | Low Dig. Sophis-tication (1) | High Dig. Sophis-tication (2) | Low Dig. Sophis-tication (3) | High Dig. Sophis-tication (4) |
| ***Acct × Post*** | **0.0060** | **-0.0023** | **0.0102** | **-0.0006** |
| | **(0.757)** | **(-0.443)** | **(0.532)** | **(-0.057)** |
| Firm × Month FE | Yes | Yes | Yes | Yes |
| Function FE | Yes | Yes | Yes | Yes |
| Clustered SE | Firm × Function | Firm × Function | Firm × Function | Firm × Function |
| Adjusted $R^2$ | 0.4793 | 0.2551 | 0.5714 | 0.2563 |
| N | 19,488 | 19,488 | 11,907 | 11,907 |

*Panel B: Demand for Permanent Positions*

| DV = | *Postings_Binary* | | *ihs(Postings_Count)* | |
|---|---|---|---|---|
| | Low Dig. Sophis-tication (1) | High Dig. Sophis-tication (2) | Low Dig. Sophis-tication (3) | High Dig. Sophis-tication (4) |
| ***Acct × Post*** | **-0.0223*** | **0.0146** | **-0.0101** | **0.0537**** |
| | **(-1.784)** | **(1.568)** | **(-0.294)** | **(2.134)** |
| Firm × Month FE | Yes | Yes | Yes | Yes |
| Function FE | Yes | Yes | Yes | Yes |
| Clustered SE | Firm × Function | Firm × Function | Firm × Function | Firm × Function |
| Adjusted $R^2$ | 0.4516 | 0.3745 | 0.6183 | 0.4509 |
| N | 19,488 | 19,488 | 11,907 | 11,907 |

Notes: This table provides results from estimating the difference-in-differences specification reported in Equation (1). The dependent variables in Panel A include only job postings seeking temporary employment, whereas those in Panel B include only job postings seeking permanent employment. Columns (1) and (2) of either panel use *Postings_Binary* as the dependent variable; Columns (3) and (4) of either panel use *ihs(Postings_Count)* as the dependent variable. The dependent variables used in Columns (1) and (3) of each panel consider job postings that require labor with low digital sophistication, whereas those in Columns (2) and (4) consider job postings that require labor with high digital sophistication. All specifications employ linear OLS regressions and include firm-month- and function-fixed effects. We present t-statistics in parentheses. Standard errors are clustered by firm-function. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% level, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in Appendix A.

**TABLE 6 Industry Digital Intensity and Accounting Labor Demand**

*Panel A: Firms in Less Digitally Intensive Industries*

| DV = | *Postings_Binary* | | *ihs(Postings_Count)* | |
|---|---|---|---|---|
| | Low Dig. Sophis-tication (1) | High Dig. Sophis-tication (2) | Low Dig. Sophis-tication (3) | High Dig. Sophis-tication (4) |
| ***Acct* × *Post*** | **-0.0445**** | **0.0254*** | **-0.0519** | **0.0970**** |
| | **(-2.395)** | **(1.793)** | **(-0.994)** | **(2.308)** |
| Firm × Month FE | Yes | Yes | Yes | Yes |
| Function FE | Yes | Yes | Yes | Yes |
| Clustered SE | Firm × Function | Firm × Function | Firm × Function | Firm × Function |
| Adjusted $R^2$ | 0.5173 | 0.4102 | 0.6602 | 0.4807 |
| N | 8,160 | 8,160 | 4,860 | 4,860 |

*Panel B: Firms in More Digitally Intensive Industries*

| DV = | *Postings_Binary* | | *ihs(Postings_Count)* | |
|---|---|---|---|---|
| | Low Dig. Sophis-tication (1) | High Dig. Sophis-tication (2) | Low Dig. Sophis-tication (3) | High Dig. Sophis-tication (4) |
| ***Acct* × *Post*** | **-0.0254** | **0.0015** | **-0.0445** | **0.0122** |
| | **(-1.355)** | **(0.100)** | **(-0.876)** | **(0.320)** |
| *p*-value (vs. Panel A) | 0.469 | 0.243 | 0.919 | 0.136 |
| Firm × Month FE | Yes | Yes | Yes | Yes |
| Function FE | Yes | Yes | Yes | Yes |
| Clustered SE | Firm × Function | Firm × Function | Firm × Function | Firm × Function |
| Adjusted $R^2$ | 0.4454 | 0.3720 | 0.6181 | 0.4465 |
| N | 8,160 | 8,160 | 5,211 | 5,211 |

Notes: This table provides results from estimating the difference-in-differences specification reported in Equation (1). Regressions in Panel A include only firms in below-median digitally intensive industries according to the Eurostat Digital Intensity Index, whereas Panel B includes only firms in above-median digitally intensive industries. Columns (1) and (2) of either panel use *Postings_Binary* as the dependent variable; Columns (3) and (4) of either panel use *ihs(Postings_Count)* as the dependent variable. The dependent variables used in Columns (1) and (3) of each panel consider job postings that require labor with low digital sophistication, whereas those in Columns (2) and (4) consider job postings that require labor with high digital sophistication. All specifications employ linear OLS regressions and include firm-month- and function-fixed effects. We present t-statistics in parentheses. Standard errors are clustered by firm-function. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% level, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in Appendix A.

**TABLE 7 Placebo Test**

| DV = | *Postings_Binary* | | *ihs(Postings_Count)* | |
|---|---|---|---|---|
| | Low Dig. Sophis-tication | High Dig. Sophis-tication | Low Dig. Sophis-tication | High Dig. Sophis-tication |
| | (1) | (2) | (3) | (4) |
| ***Acct × Post*** | **-0.0188** | **0.0025** | **-0.0714** | **0.0166** |
| | **(-1.016)** | **(0.174)** | **(-1.549)** | **(0.415)** |
| Firm × Month FE | Yes | Yes | Yes | Yes |
| Function FE | Yes | Yes | Yes | Yes |
| Clustered SE | Firm × Function | Firm × Function | Firm × Function | Firm × Function |
| Adjusted $R^2$ | 0.4629 | 0.3722 | 0.6443 | 0.5087 |
| N | 8,304 | 8,304 | 5,286 | 5,286 |

Notes: This table provides results from placebo tests estimating the difference-in-differences specification reported in Equation (1) using a sample of Swiss firms. Columns (1) and (2) use *Postings_Binary* as the dependent variable; Columns (3) and (4) use *ihs(Postings_Count)* as the dependent variable. The dependent variables used in Columns (1) and (3) consider job postings that require labor with low digital sophistication, whereas those in Columns (2) and (4) consider job postings that require labor with high digital sophistication. All specifications employ linear OLS regressions and include firm-month- and function-fixed effects. We present t-statistics in parentheses. Standard errors are clustered by firm-function. $^{***}$, $^{**}$, and $^{*}$ denote two-tailed statistical significance at the 1%, 5%, and 10% level, respectively. Continuous variables are winsorized at the 1$^{st}$ and 99$^{th}$ percentiles. All variables are defined in Appendix A.