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Human + AI in Financial Reporting: Early Evidence from the Field

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Abstract

This paper studies the usage of AI in financial reporting. We partner with a technology startup that provides AI tools to accountants. We combine field data from 74 companies with hundreds of thousands of transactions and survey data from 277 accountants in the US to understand how this growing technology is incorporated into accounting processes, especially in transaction analysis, at both the task and transaction level. We provide the following early evidence: 1) 38% of survey participants report having fully or partially integrated Generative AI into their workflows, including financial reporting tasks. 2) Generative AI usage is associated with a 66% increase in the number of clients supported in the same week, with accountants reallocating approximately 10% of their time from routine tasks to business communication and quality assurance. 3) AI adoption is associated with a 4-day reduction in the time required for monthly financial reporting. 4) Experienced accountants tend to use these tools more frequently but remain cautious about relying on them for complex tasks (e.g., accruals). 5) The LLM-powered AI software generates high-confidence scores for validated transactions, efficiently auto-categorizes accounts without specific rules, and integrates data from multiple sources using machine learning.

Keywords: Generative AI, Financial Reporting, Accountant, Technology Adoption, Large Language Model, Human + AI

JEL Classification: O33, M41, M54, C45

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1. Introduction

The adoption of Artificial Intelligence (AI) in financial reporting by accountants is experiencing significant growth, with the potential for even greater expansion in the near future.[1] There is a growing need for the discourse surrounding AI, especially Generative AI, to shift from *whether* AI should be adopted, to a practical exploration of *how* it can be implemented and leveraged effectively. Much of the existing research on this topic relies on firm-level data, often treating the shift to AI as a black box, thereby overlooking the nuanced impacts at the individual worker and task levels (Fedyk et al., 2022; Ashraf, 2024). Those studies leave key questions about the micro-level dynamics of this change unaddressed. Specifically, there is limited understanding of how AI adoption affects individual accountants, their tasks, and the day-to-day processes. This study utilizes worker-task level data to provide early evidence of what this transition looks like on the ground. By examining this micro-level interaction between AI usage and accounting workflows, this paper aims to shed light on the evolving relationship between human accountants and AI technology in financial reporting, offering valuable evidence that can inform both future academic research and practical applications in the field.

This paper explores the current status of AI in accounting through four key lenses: (1) the adoption and perceptions of AI among accountants, (2) its effect on labor productivity and task reallocation, (3) its potential to influence the quality of financial reporting, and (4) the interactive effects between human expertise and AI technology.

Our empirical approach to addressing these questions follows a multi-method strategy, utilizing data from the field (Bloomfield et al., 2016) to capture the evolving nature of Generative AI tools

[1] According to an early 2024 report by Thomson Reuters, approximately 23% of 1,128 surveyed accountants were already using AI or had active plans to employ AI tools in their day-to-day work. A third of the respondents indicated that they were considering AI usage. These number have only grown since Jan/Feb 2024.

in accounting. First, we partner with a company (hereafter: Partner Firm) that supplies Generative AI technology to gain a meaningful understanding of the technological aspects of AI in accounting. The proprietary internal data from our Partner Firm exists at the accountant, task, and transaction level. We utilize this data to analyze how human accountants engage with AI tools when carrying out accounting work. Notably, granular transaction-level data reveals how AI is reshaping the foundational element of financial accounting – transactional analysis. Second, we utilize the survey approach to more broadly explore the usage of Generative AI in accounting, particularly where accountant-level task data is difficult to obtain directly. Our surveys help uncover how accountants allocate their time across various tasks, providing a clearer picture of the shift in workload as a result of AI integration.

The sample firms in our study are small and mid-sized companies, offering a unique opportunity to explore AI adoption and innovation in organizations that may be less studied in the literature (Minnis and Shroff, 2017). This perspective is valuable because it sheds light on how Generative AI is transforming accounting processes within smaller firms – where AI adoption may differ in scale and scope compared to large corporations.

a. The Current Status of AI Utilization in Accounting

Generative AI technologies are increasingly being incorporated into accounting practices, though their usage varies even within the profession. Anecdotally, possible usages range from data entry automation and anomaly detection to advanced predictive analytics and decision support systems. Academic studies have shown suggestive evidence that AI may be used to generate textual disclosures or analyze large datasets to predict earnings (Blankespoor et al., 2024; Kim et al., 2024). However, the pace of adoption and the types of AI tools used are not uniform across accountants or accounting tasks. Some accountants utilize basic automation for routine tasks, while others

engage in more complex analytics that inform strategic decision-making. Furthermore, the perceptions of accountants toward AI are equally varied, shaped by their own experiences and levels of expertise: while many accountants view AI with cautious optimism, recognizing its potential to reduce repetitive work and enhance decision-making, many share concerns about job displacement, data security, and the potential for AI to perpetuate biases in decision-making. Understanding these perceptions and the factors influencing them is crucial for assessing the long-term implications of AI on the profession. In short, AI is rapidly being adopted in the accounting profession, and it is manifesting in a variety of ways. However, despite the growing body of anecdotal evidence, we still lack a comprehensive understanding of the full scope of these changes and their long-term implications for the profession. The absence of robust panel data makes it difficult to draw definitive and quantitative conclusions about the efficiency gains associated with this technological shift.

To our knowledge, this is the first study to provide direct and descriptive evidence on accountants' engagement with Generative AI tools in their day-to-day work processes. Section 2 provides a more in-depth discussion of Generative AI technology in the context of this study. Here we highlight several key features of Generative AI, drawing on the internal data from our partner firm as an example. One notable application of Large Language Models (LLMs), the foundational model for Generative AI, in financial reporting is autocategorization, which differs from traditional rule-based approaches. Unlike rule-based systems, which follow predefined protocols, AI-powered tools can categorize transactions dynamically without relying on strict rules. For instance, QuickBooks, a popular accounting platform, offers a basic rule-based model. QuickBooks is unable to categorize a transaction type when supplied the amount, transacting parties, and brief descriptions of those transactions. In contrast, several AI-powered platforms leverage LLMs to

categorize transactions by analyzing public information about the contracting party, without the need for predefined rules. Another notable advancement of the Partnering Firm's technology is the employment of both basic machine learning and reinforcement learning, utilizing historical transaction data combined with human input. These systems typically provide a confidence score to guide human decision-making. These scores reflect the AI's confidence in its data and pattern recognition, with higher scores assigned to transactions that are validated by multiple data points or involve frequent contracting parties.

We survey 277 accountants on how they use Generative AI for different accounting tasks. These tasks include data entry, financial reporting, learning & training, financial analysis, business communication, quality assurance, administrative work, and advisory services. Across our survey respondents, the median accountant uses Generative AI tools occasionally (1-2 days a week), less than 10 percent of accountants never use Generative AI in their work, and the top 10 percent of accountants report using Generative AI numerous times per day and that it is a core part of daily work. Similar to the heterogeneity in usage, we find variation in their perception of the value of generative AI. We consider three dimensions of value: time savings, breadth of application, and accuracy. For time savings, the mode of respondents (26 percent) believe there are moderate time savings (i.e. reduction of 21 to 40 percent). For breadth of application, the median accountant believes that generative AI can be widely helpful for routine tasks (i.e. 21-40 percent replacement by AI) and the classification of transactions (i.e. 21-40 percent automatic categorization), but that there is also disagreement about the extent of its usefulness. In terms of accuracy, we find that accountants believe that generative AI may substantially decrease the number of accounting errors. The median response is that generative AI is expected to decrease errors by 21-40 percent, but there is substantial dispersion.

b. The Impact of AI on Labor Productivity and Task Reallocation

AI's most immediate effect on accountants is likely to be seen in productivity metrics and the reallocation of labor. While AI has the potential to automate repetitive and time-consuming tasks, such as data entry and transaction matching, it also presents opportunities for accountants to shift their focus toward more value-added activities. The automation of routine tasks may lead to substantial time savings, which could be redirected toward tasks such as financial analysis, consulting, client relationship management, or quality assurance. This shift in task allocation reflects a broader trend in the accounting profession where technology is increasingly used to augment human expertise rather than replace it. However, the degree to which AI can improve productivity depends on a variety of factors, including the quality of AI tools, the level of training provided to accountants, and the extent to which AI is integrated into the organizational workflow. Economically, firms that adopt AI more extensively may see lower operational costs, improved efficiency, and an enhanced ability to scale their services without a proportional increase in headcount.

We show that accountant AI usage is associated with greater productivity: supporting more clients simultaneously and having more billable hours. These findings corroborate the surveyed perceptions of accountants about the value of Generative AI. Further, we survey accountants on how they use Generative AI for different accounting tasks. These tasks include data entry, financial reporting, learning & training, financial analysis, business communication, quality assurance, administrative work, and advisory services. We show that Generative AI is an important tool that is frequently used by some accountants and that its use is associated with spending less time on data entry, financial reporting and financial analysis, but more time on business communication, quality assurance and administrative work.

c. The Effect of AI on Financial Reporting Quality

One of the most significant potential outcomes of AI adoption in accounting is its impact on financial reporting quality. AI systems, particularly those using machine learning and predictive analytics, can potentially process vast amounts of data far more quickly and accurately than human accountants. This capability has the potential to reduce errors in financial statements, enhance the consistency of reporting, and improve the overall quality of financial information. In particular, Generative AI tools that automate routine tasks such as reconciliations, transactions, and the identification of anomalies can help ensure that financial statements are free from basic errors or inconsistencies, which can undermine their credibility. At the same time, however, there are concerns that overreliance on AI might lead to unintended consequences. For instance, if AI systems are not properly trained or if biases are inadvertently built into the algorithms, the quality of financial reporting could suffer. This is particularly pertinent in contexts where human judgment plays a crucial role in interpreting complex or ambiguous data. As LLMs become more sophisticated, it is essential for firms to strike a balance between leveraging the efficiencies of AI and ensuring that human oversight remains in place to catch errors or biases that AI might miss systematically.

With tens and thousands of transaction level data, this study can meaningfully contribute to the discourse on the extent to which AI enhances financial reporting quality. Analyzing proprietary data by the Partner Firm, we measure the persistence of earnings for each client from month to month, we tabulate the granularity and uniqueness of account types, and we examine the length of time it takes to close the books each month. We find that generative AI improves the persistence, informativeness and timeliness of financial reporting across the board.

d. Interactive Effects: Human Expertise and AI Technology

The final key area explored in this paper is the interactive effect between human accountants and Generative AI technologies. While AI has the potential to automate many aspects of accounting, it is unlikely to fully replace the need for human expertise, particularly in complex or judgment-intensive tasks. In practice, AI and accountants often work in tandem, with the human element providing oversight, interpretation, and intervention when necessary. We find that there is a strong positive trend to AI utilization for both experienced and inexperienced accountants. We also find that more experienced accountants tend utilize AI tools more and they also play a relatively more critical role in reviewing, verifying, and overriding AI-generated outputs when necessary. This dynamic suggests that the interaction between human accountants and AI is not purely complementary, but rather a more complex interplay in which human expertise enhances the effectiveness of AI, and vice versa. Economically, this raises the question as to whether Generative AI is complementary to experienced or inexperienced accountants or both.

In sum, this paper seeks to contribute to the growing body of research on the intersection of AI and accounting in three important ways. Primarily, we provide early empirical evidence on the adoption and impact of Generative AI technologies in financial reporting. While much of the existing literature is based on anecdotal evidence or focuses on settings outside of financial reporting, our study offers a quantitative overview on the extent of AI adoption. With our finding of a 38% adoption rate of Generative AI amongst accountants, it is important to provide rigorous, data-driven insights into how these technologies are reshaping financial reporting practices. By partnering with a firm that is pioneering the Generative AI revolution, we are able to look into the black box and better understand, in great detail, how and the extent to which accountants are engaging with this technology.

In addition, this paper is one of the first to extend the current academic discourse regarding Generative AI's impact on accounting beyond that of its ability to process information. Contemporaneous studies (Kim et al., 2024) largely focus on the role of large language models (LLMs) like BERT, ChatGPT, Ollama, and Gemini in processing a large amount of data (and often text data). Our study, however, indicates that Generative AI technology will not only enhance the analysis of narrative data but also fundamentally alter the preparation of quantitative financial reporting numbers. This shift could have profound implications for financial analysis, forecasting, and decision-making.

Finally, through a comprehensive analysis of survey data and field data, we aim to provide a clearer understanding of the ongoing transformation of the accounting profession in the age of AI. By shedding light on these four key areas – adoption patterns, labor productivity changes, financial reporting quality, and human-AI interaction – we offer valuable insights into how AI will shape the future of accounting and the broader implications for labor, firms, and regulatory bodies.

While our study provides important insights into the early adoption and impact of Generative AI in financial reporting, several caveats must be considered when interpreting the results. First, the key limitation of our study is that the usage of Generative AI in financial reporting is likely endogenous. Firms and accountants that adopt AI technologies may differ systematically from those that do not, making it challenging to isolate the precise causal effects of AI adoption on financial reporting outcomes. Second, the number of firms used for our analyses is relatively small. While our use of proprietary accounting data from multiple companies represents an advantage over studies that rely on publicly available data, the sample size may limit the generalizability of our findings. Third, given the early stage of AI adoption in financial reporting, it is important to recognize that the full impact of these technologies may not yet be fully realized. As more firms

adopt Generative AI and its capabilities evolve, future research can track changes in financial reporting practices, providing deeper insights into the long-term effects and identifying any unintended consequences that may arise as AI systems become more integrated into accounting workflows. Finally, our paper implicitly suggests several hypotheses about the interaction between human accountants and AI. However, testing these hypotheses was not the primary focus of our study. We believe that the suggestive evidence is interesting and provides a foundation for future research to explore more systematically.

The remainder of this paper is structured as follows. Section 2 provides an overview of the relevant institutional setting, including details about our partner firm, the specific aspects of AI technology under investigation, and other accountant- and task-level contexts. Section 3 reviews the existing literature pertinent to our study and conceptual underpinnings. Section 4 outlines the research design, presents the results and offers interpretations of the findings. Finally, Section 5 concludes.

2. Institutional Setting

a. Overview of the Partner Firm

Our Partner Firm is a San Francisco-based startup that leverages Generative AI technology to help companies improve their accounting operations. Founded in 2022, with the goal of transforming the accounting industry, the company's mission is to "Bring Generative AI to power accounting workflow automation." Since its launch, the Partner Firm has assisted over 100 companies in implementing AI-driven accounting solutions. These solutions encompass a variety of tasks, such as automating the classification of transactions from bank and credit card data, identifying accrual entries and generating work papers, summarizing contracts, integrating relevant information into workflows, and matching supporting documents for journal entries and reconciliation schedules. These accounting functions are, by nature, repetitive, tedious, and prone to human error.

By automating the traditionally manual processes of bookkeeping and financial record-keeping, the Partner Firm helps accountants and clients reduce costs and improve the accuracy and efficiency of their processes.

The business model of our Partner Firm has 2 complementary prongs. First, the firm directly serves client organizations by providing outsourced bookkeeping and financial record-keeping through its in-house accounting team. Second, it licenses its Generative AI technology to external accounting firms, enabling their accountants to manage bookkeeping and financial record-keeping for the clients of those firms. The key distinction between the two models lies in the presence of an intermediary accounting firm between our Partner Firm and the end client. In both cases, whether the accountants are in-house or external, they share similar qualifications (e.g. education in accounting), perform analogous functions (e.g. bookkeeping), and utilize the same integrated toolset: a baseline accounting software (e.g. QuickBooks), combined with Generative AI technology that is provided by the Partner Firm.

b. Technological Foundation

At its core, the Partner Firm's technology combines various Artificial Intelligence (AI) models – particularly Large Language Models (LLMs) and Deep Learning (DL) – to contextualize and process accounting data in ways that were previously only possible through skilled human labor. Below is a more detailed primer of the different technological components that power the Partner Firm's product.

i. Generative AI and Large Language Models (LLM)

Generative AI refers to algorithms capable of producing new content or data that mirrors the underlying patterns or structures of existing data. For our Partner Firm, this involves using Generative AI models to "understand" the language of financial documents – such as invoices,

receipts, bank statements, and general ledger entries – and generate accurate accounting records from them. This is accomplished through Large Language Models[2] (LLM), a branch of AI that focuses on enabling computers to process and analyze human language.

This technology can facilitate text extraction and understanding. This has traditionally been difficult to fully automate for several reasons. First, financial documents often come in unstructured and inconsistent formats, such as PDFs, scanned images, or emails, making it difficult to extract useful data. Second, information necessary to contextualize data, such as vendor description or transaction types, often doesn't exist in a predetermined databank and requires idiosyncratic knowledge or a broader search. Traditional OCR (Optical Character Recognition) software might be able to recognize text, but it lacks the ability to understand the context or relationships between the data. Prior to the introduction of Generative AI, popular machine learning methods such as Naïve Bayes or basic neural networks were able to automate some accounting functions but only in a closed-end sense: there needed to be an prespecified ecosystem of rules and patterns.

On the other hand, the Partner Firm's product, integrates sophisticated LLMs that do more than just extract words; they interpret the meaning behind them. For example, their model can differentiate between an invoice for services, a sales receipt, and a payroll document, recognizing key elements like dates, amounts, parties involved, and transaction types. Beyond simply extracting data, the Partner Firm's AI also understands the context in which the data appears. For example, the model is capable of distinguishing between a sales transaction and an expense, even

[2] The LLMs specifically utilized by the Partner Firm include GPT-4o for zero-shot cases and GPT-3.5 fine-tuned for multi-shot cases. The GPT-3.5 fine-tuned model will likely be utilized in the pipeline to accurately represent and capture client specific information. The GPT-3.5 model can be continuously adapted over time to the firm, though it is unclear if this is a feature of the stack. Gpt-4o is likely used in scenarios where its expansive representation space is required. Likely machine learning models present in various pipelines include k-means clustering for grouping similar items and identifying outliers, and support vector machines for classifying which financial documents are queried and extracting key information.

if they appear in similar formats or fields, allowing it to correctly categorize and classify each transaction. This ability to categorize and understand context minimizes human error and ensures greater accuracy when simultaneously processing large volumes of documents in an instant.

ii. Machine Learning, Classification, and Accounts Reconciliation

The primary setting for our study is the bookkeeping service, which forms the foundation of our Partner Firm's offerings, utilizing AI to automate the entire process from document intake to month-end close. Through advanced algorithms, Generative AI technologies can streamline activities such as extracting and gathering data, transaction categorization, data reconciliation, and financial reporting, leading to increased efficiency and accuracy.

In the example of transaction matching and reconciliation: when new financial data is fed into the system, the technology will work to automatically match transactions recorded in the company's accounting system to entries in external documents like bank statements. For instance, if a business makes a payment for supplies, the AI will automatically find the corresponding entry in the bank statement. It will also ensure that discrepancies – such as unrecorded fees or missing transactions – are flagged for further review. This significantly reduces the manual effort involved in reconciliation and ensures that financial data remains accurate and up to date. In traditional accounting, accountants must manually categorize transactions into various categories like revenue, expenses, assets, liabilities, and equity. Our Partner Firm's AI system utilizes public data (e.g., contracting party's information per Wikipedia, for example) as well as past transactional data to predict and classify new transactions into appropriate categories. For example, if an AI model recognizes that a specific vendor's invoice typically represents an expense for office supplies, it will automatically classify similar future invoices in the same way. The system also provides

confidence scores based on the quality of data and pattern recognition. Figure 1 Panel A provides an example of auto-categorization by the Generative AI system.

Furthermore, the technology can intelligently handle pattern recognition for accruals and anomalies. Over time, the AI learns the patterns of a business's typical financial transactions. For example, the system may learn that the company generally receives payments from a specific vendor on the first of every month or that payroll is typically processed on Fridays. First, this pattern recognition allows the AI system to automatically prompt accrual recognitions, as illustrated in Figure 1 Panel B. Additionally, any deviation from these patterns, such as unexpected payments or irregular spending, may be flagged as an anomaly. This functionality helps the business identify potential errors or unusual financial activity in real time, reducing the risk of financial misreporting. To further enhance the AI's understanding, the Partner Firm's platform uses machine learning to build its own taxonomy of financial terms and transaction categories. Over time, the AI learns the typical structure of accounting workflows and can adapt to new financial scenarios. For instance, if an accountant submits a new type of expense category or financial report, the AI will recognize the need to learn from this new input and adjust its processing accordingly (Bai et al., 2022).

iii. Accounting Technology Analysis

For the purposes of this study, it is essential to validate the Partner Firm's AI technology to ensure its reliability and relevance in the context of the research. This validation is crucial because the central objective of the study is to explore the impact of the latest advancements in artificial intelligence (AI) on accounting work and its outcomes. To draw meaningful conclusions about the effects of AI on accounting processes, it is necessary to ensure that the technology being studied is both functional and effective.

To evaluate this quality, we use a set of 272 arbitrary accounting transactions provided by a third party and horse race various accounting software. We consider the following accounting software tools: QuickBooks Online, Peer 1, Peer 2, and the Partner Firm. All of these accounting software tools automatically categorize transactions, but they do so to varying degrees of comprehensiveness. Figure 2 shows the fraction of the 272 transactions that were categorized by each of the software tools. QuickBooks Online, which uses user-defined rules and historical data, failed to automatically categorize any of the transactions. Peer 1 relies on machine learning models with user inputs and managed to categorize 37 percent of the transactions. Peer 2 combines a mixture of rules and large language models and categorized 65 percent of transactions. Finally, our Partner Firm that uses Generative AI succeeded in categorizing 97 percent of transactions. The difference in performance stems from the underlying technology in face of this type of unstructured data. Our Partner Firm's software was the only system that was able to draw on historical data and generate a 'knowledge graph' in order to contextualize the transactions. This process is specific to AI and is informally referred to as 'hydrating the data' – where the AI technology first 'ingests' the truncated signal (i.e. in this case, the unstructured transactions) and then builds a knowledge graph based on both historical data (e.g. past similar transactions) and external search (e.g. vendor information), and finally uses the knowledge graph to 'hydrate' the truncated signals into an accurate outputs. Figure 3 describes the system architect of the Partner Firm for financial reporting. In addition to the comparison test, we empirically examine the determinants of output accuracy produced by the Partner Firm's AI technology. In Table 1, we show how the accuracy of AI-automated transaction categorization, as measured by confidence scores, varies with certain input characteristics. These input characteristics include whether the system was able to match documentation (e.g. bank statements), length of description as measured by words (e.g. vendor

description in credit card information), payee frequency, and the expense designation associated with the transaction. Columns 1 through 4 present models with progressively more stringent fixed effects structures. We show that across all models, a higher matched score is positively and statistically significantly associated the confidence score. The effect size is small for description length, indicating that it is not an important predictor for output accuracy. Perhaps most interestingly, when controlling for temporal, payee, and account level factors, payee frequency is positively and significantly associated with confidence score. This is consistent with AI drawing from extant context to weave a 'knowledge graph' in predicting future outputs. By analyzing these determinants, we gain deeper insights into the nature of AI performance, offering a more comprehensive understanding of the tool's reliability and effectiveness in accounting tasks.

It's important to note that, validating the Partner Firm's AI technology is not only a necessary step to ensure the reliability of the study's findings, but it also supports the broader goal of this study to shed light on the black box that is AI-assisted accounting. By examining and contrasting different accounting tools, each driven by distinct underlying mechanisms, we underscore that AI in accounting extends beyond traditional rule-based systems, machine learning, and even large language models. Specifically, AI in this context leverages advanced contextual understanding and sophisticated knowledge graphs, enabling it to produce more accurate and insightful outputs than other available technologies. This capacity to integrate and interpret complex information allows Generative AI to outperform conventional tools, offering new possibilities improvements in accounting.

Our subsequent empirical analyses (Section 4) where we evaluate the real impact of Generative AI on accountant productivity and work outcomes is a joint hypothesis test of the quality of the Generative AI tool we study and its real effects. Therefore, confirming the functionality of the

Partner Firm's AI technology is not just a preliminary step, but a critical foundation for the study's credibility and for ensuring that the findings can provide meaningful insights into the evolving role of AI in accounting practices. Figure 2 shows that both in absolute terms and relative terms, our Partner Firm's Generative AI meets the necessary but insufficient condition of being a high-quality tool.

c. Boutique Accountants and Private Firms

The accountants that are examined in this study are either accountants employed directly by our Partner Firm or accountants who work at boutique accounting firms that license the AI technology of our Partner Firm. These accountants predominantly serve private U.S. companies, which span a broad range of industries and have total assets averaging 1.3 million up to 10.8 million. These businesses outsource various accounting functions – including maintaining comprehensive accounting records, preparing periodic financial reports, ensuring tax compliance, and interpreting accounting standards – to the accountants in our study.

There are clear trade-offs in focusing on small and mid-sized private companies: these firms are numerous and account for a large share of the U.S. economy in terms of dollar value as well. However, information regarding their accounting practices is often scarce, as they are subject to less stringent transparency requirements compared to public companies (Minnis and Shroff, 2017). Nevertheless, private enterprises are widely regarded as a critical driver of economic growth (Haltiwanger et al., 2013). Due to the significant disparity in transparency obligations between public and private companies, there is limited understanding of the accounting processes and the quality of financial reporting within the types of firms included in this study.

3. Related Literature and Conceptual Underpinnings

a. AI's Application in Accounting

In recent years, Artificial Intelligence (AI) has advanced considerably with its applications in accounting, including financial analysis and reporting, transitioning through machine learning (ML), robotic process automation (RPA), natural language processing (NLP), and large language model (LLM), which is the foundational model for Generative AI. Recent research by Kapoor et al. (2024) and Anica-Popa et al. (2024) illustrates anecdotally how Generative AI models, particularly OpenAI's ChatGPT, have improved accounting task performance, underscoring AI's transformative potential for the accounting industry.

Machine learning (ML) algorithms excel at identifying hidden patterns in data without the need for explicit programming. They greatly enhance financial statement analysis, KPI forecasting, and anomaly detection. Chen et al. (2022) predict earnings changes using machine learning with XBRL data. Binz et al. (2024) emphasize ML's contribution to improving earnings forecasts and market trend analyses. Additionally, ML plays a crucial role in fraud detection and risk management, ensuring the integrity of financial reporting (Bertomeu et al., 2021).

Robotic process automation (RPA) is another key advancement. It automates repetitive, rule-based tasks in financial reporting, such as data extraction and report generation. By mimicking human actions, RPA improves process compliance, reduces errors, and boosts efficiency. Studies like Yao (2024) highlight RPA's benefits, including cost reduction and increased accuracy, which have the potential to transform accounting workflows (Cooper et al., 2019).

Natural language processing (NLP) enables machines to understand and generate human-like text, enhancing the process and creation of qualitative financial insights (Dyer et al., 2017). NLP techniques can process text data with financial data, supporting topic analysis and sentiment analysis. Araci (2019) developed FinBERT, a pre-trained language model for financial sentiment analysis, specifically designed to understand the specialized language in accounting and finance.

NLP-powered chatbots also have a potential to improve stakeholder engagement by delivering personalized insights and explanations, making financial information more accessible. Recent work by Brynjolfsson et al. (2024) explores the impact of such chatbots on worker efficiency and workplace dynamics, albeit outside of a financial setting.

Building on a Large Language Model (LLM) as the cornerstone, Generative AI affects and enhances not only the processing but also the generation of vast amounts of data, including numbers, text, voice, and images (Kim et al., 2024). AI-based systems, also known as AI agents, represent a significant advancement over traditional language models. Unlike isolated models, AI agents function as integrated systems (Kapoor et al., 2024). These agents can combine various external tools, such as the internet and SQL databases, with ML/AI models. These tools and models are coordinated by a central control mechanism to handle complex, context-dependent tasks in financial reporting and accounting. An important feature of AI agents is that their decision-making process is inherently stochastic, meaning that performance can improve through repeated runs.

A relevant paper to this study is Anica-Popa et al. (2024), which presents a framework for an LLM-based internal generative AI system designed specifically to interact with accountants and auditors, highlighting one company's experimentation with this system. This system consists of several components: 1) a Large Language Model (LLM) as its controlling mechanism 2) a System Data Source providing in-house data and information 3) a Knowledge Consolidator that continuously updates the system's knowledge base from internal and external sources (e.g. the internet), and a Filtering (Security) Layer ensuring data confidentiality. The commercialized technology used by our Partner Firm incorporates elements of all these advancements. This is particularly significant, as the accountants observed in this study are regularly utilizing this sophisticated technology in their day-to-day work. Our paper examines the effects of integrating AI into the financial

bookkeeping and reporting processes. To the best of our knowledge, this is the first academic study that provides a quantitative analysis of how accountants incorporate generative AI technology as an integral part of their financial reporting workflow.

b. Conceptual Underpinnings

To the best of our knowledge the extant literature is silent regarding the impact of generative AI on accounting processes including accounting labor workflow and financial reporting activities. This gap can be attributed to two primary factors: first, the adoption of generative AI in practice is a relatively recent phenomenon, and second, the lack of accessible, granular data on accounting processes has limited empirical research in this area. We draw on existing studies that examine the application of AI in other settings to inform the conceptual underpinnings for our analyses. These studies provide valuable insights into how AI can influence labor dynamics, task automation, human interaction, and work product – insights that can be adapted to the context of accounting.

i. Technology Adoption in Accounting

Technology adoption is perceived as a major driver for economic growth, but the technology adoption process at the macro level (e.g., country and industry) is gradual and often slow. Multiple factors determine technology adoption decisions: returns, constraints, choices, and beliefs (Foster and Resenzweig, 2010). Humlum and Vestergaard (2024) document a huge variation in adopting ChatGPT across different occupations. Their paper observes that high skilled and IT-tilted occupations, such as software developers, adopt generative AI tools (e.g., ChatGPT) in their workflow faster, whereas for certain other occupations employers may restrict this adoption. Given this, accounting standards and considerations for quality assurance would primarily shape the adoption of generative AI tools within the accounting profession. Secondary to the regulatory environment, as the product market for AI-powered accounting software evolves and becomes

increasingly competitive, accountants may face a plethora of choice before starting the costly integration of a new tool into their workflow. One thing is clear: the adoption rate of ChatGPT is faster than any recently commercialized technology, underscoring the urgent need to address the adoption of generative AI in accounting.

ii. Accounting Labor Productivity

The impact of generative AI on labor productivity and workflow is conceptually two-fold. First, there is a substitutive effect, where AI technologies replace or automate certain tasks that were previously performed by human workers. Second, and perhaps more subtly, there is an interaction effect between AI technologies and human workers, whereby AI augments human capabilities, enhancing productivity through collaboration rather than replacement.

This intuition echoes Autor et al. (2003) – in their seminal study, the authors argue that technology can both substitute the readily codifiable (i.e. procedural and rules-based) work and complement more complex and nonroutine work. Acemoglu and Autor (2011) extends this foundation and argue that technology can shift demand unevenly for high and low skilled worker. These theories are grounded in empirical reality. Brynjolfsson et al. (2024) show that generative AI boosts the productivity of customer support agents by reducing the average time required to resolve issues by 14 percent, with low skilled works driving much of that difference (34%).

We extend this genre of work and apply the same concepts to our setting by considering two dimensions of accounting labor. At the task level, we have more routine/procedural tasks (e.g. data entry) vs. more complex/strategic tasks (e.g. analysis). At the accountant level, we study a continuum of accountants differentiated by accreditation (e.g. CPA) and experience (e.g. years worked). We conjecture that generative AI may be useful for accountants with different levels of expertise. We do not make explicit predictions about where efficiency gains will be most

pronounced. On one hand, these gains may be more noticeable among highly skilled accountants. Even with advanced technology, no accounting process is fully automated. For instance, human verification or intervention becomes even more imperative for automate expense categorizations. On the other hand, tools like automated data entry and reconciliation could yield substantial time savings, effectively lowering the demand placed on a more junior accountant who may be responsible for those routine and codifiable tasks.

iii. Accounting Processes and Quality

Potential expedition of accounting processes would result from the automation of repetitive tasks. In the context of data entry, Generative AI can automate the extraction of data from invoices, receipts, and other financial documents using Optical Character Recognition (OCR) and Natural Language Processing (NLP). This reduces the need for manual data entry, significantly speeding up the process. In the context of transaction analysis, AI can analyze large volumes of transactions at high speed, identifying trends, anomalies, or patterns that would take human accountants much longer to detect. This allows for faster insights and decision-making. In the context of categorization and reconciliation, AI can automatically categorize transactions based on historical data and predefined rules, reducing the time accountants spend on classification. It can also reconcile accounts by matching transactions across records, ensuring accuracy while eliminating manual checks.

At the task level, these AI tools can free up accountants to focus on higher-value work like quality assurance, financial analysis, forecasting, and strategy by automating time-consuming, routine tasks. This would lead to biased reallocation of human capital, with the demand for accounting labor to be shifted towards more high skill tasks such as quality assurance, decision-making, and

advisory. In the context of financial reporting quality, this may lead to improved informativeness and timeliness of financial reporting.

On the other hand, one may not expect to see expedited accounting processes as a result of Generative AI due to reasons such as integration challenges, poor data availability, dependence on human oversight, or other costs of implementation. For example, integrating generative AI into existing accounting workflows can be complex and costly. Many organizations rely on legacy software, and AI tools often require customization to fit the specific needs and workflows of an organization. Further, AI relies on high-quality, structured data to function effectively. Inaccurate, incomplete, or inconsistent data can lead to errors, undermining the potential benefits of automation (Cowgill et al., 2020).

iv. Human + AI in Accounting

The interaction of humans with AI has been studied in accounting and finance settings. Costello et al. (2020) show that machine-based lending models combined with experienced human users can lead to better lending outcomes. Their study emphasizes the importance of both hard and soft information. Another study, McLaughlin and Spiess (2022), shows that humans find it costly to deviate from machine outputs even when the output is wrong, which arises from an agency problem where the human is disinclined to be audited. In our case, this is particularly relevant because human accountants are required to double-check AI outputs frequently, the time savings could be minimal or further nullified by the human's reluctance to intervene. As we discuss when describing the Partner Firm's technology, a confidence score is generated and displayed alongside automated prompts such as expense categorizations. The human accountant uses this confidence score to determine their extent of utilization and/or intervention; the machine learns from the

human's actions in generating future output. This two-way learning represents another layer of sophistication in the interaction between human and AI in accounting (Fassi and Srinivasan, 2024).

4. Research Design and Findings

This paper examines the state of AI in accounting from four perspectives: (1) the adoption/usage and attitudes of accountants toward AI, (2) its impact on labor productivity and task redistribution, (3) its potential to enhance the quality of financial reporting, and (4) the interactive effects between human expertise and AI technology. Below we describe our data source and sample constructions. Then we outline our methodology, findings, and interpretations in relation to each of these aspects.

a. Data

This study draws on two primary sources of data for our empirical analysis: survey data gathered directly from accountants and proprietary field data obtained through the Partner Firm. A diagram outlining these data types and their sources is presented in Figure 4.

We administer surveys to three distinct groups of accountants using the Qualtrics survey platform. The first group consists of internal accountants employed by the Partner Firm, who provide services to external clients such as startups and small-to-medium-sized businesses (SMBs). Their primary responsibilities include bookkeeping, financial reporting, and managing the month-end closing of financial records. The second group includes external accountants employed by accounting firms that license the AI technology from the Partner Firm. These accountants perform similar tasks to the first group, using the same tools and serving a comparable clientele. The third group consists of (external) accountants from (accounting) firms with no direct affiliation to the Partner Firm. While their client base and work processes are similar to those of the first two groups, they utilize a variety of unobserved technologies in their day-to-day work.

We also gather field data at the accountant, task, and client levels from the Partner Firm. This data specifically pertains to the first group of surveyed accountants – internal accountants at the Partner Firm responsible for managing bookkeeping and financial reporting for small businesses. We collect financial records from these firms both before and after the implementation of AI technology. In addition, we obtain the underlying transaction data that comprises these aggregate financial records, including detailed expense line items. For each line item of transaction data, we also collect the relevant metadata, such as the AI-suggested expense category, the associated confidence score, and any interventions made by the human accountant.

b. Survey Instrument

To study the impact of generative AI on accounting professionals, we employ a set of longitudinal survey instruments tracking weekly workflow changes over November 2024. In our survey design, we have two groups of participants. The first group comprises of participants who are affiliated with the Partner Firm. This includes 9 internal accountants who have integrated the Partner Firm's proprietary AI tool into their workflow, along with 2 external accountants who are newly adopting this technology. For the other group, we partnered with established academic research platforms Prolific and Connect. This group yielded 266 verified accountants to ensure adequate statistical power for our analyses.

Our survey protocol implements a five-wave design to capture AI adoption and work patterns. Appendix B shows the three sets of surveys (i.e., pre, weekly, and post) administered over the course of our study. The first survey, the pre-assessment, establishes critical baseline measures spanning AI integration patterns, professional context, and demographics. We collect information on years of accounting experience, sectors, and the client portfolio size that the participant serves. This baseline data enables us to control for varying experience levels while measuring efficiency

gains. This is followed by three weekly tracking surveys that capture work patterns. The questions in the weekly surveys focus on the accountants' work processes such as allocation of time between types of tasks. To conclude, the post-survey is administered after the three weekly surveys and focuses on gathering insights into the accountants' expectations of the AI tool. Participants estimated potential performance improvements across four dimensions: expected reductions in task completion times, percentage of tasks suitable for automation, accuracy rates for AI-driven transaction classification, and anticipated decreases in error rates. These estimates establish ranges for what practitioners anticipate AI's impact to be, based on their direct experiences and expectations. Such bounds are valuable even if they deviate from empirical observation, as they capture the accounting profession's current expectations and risk tolerance for new AI technologies as they integrate into accounting practices. Understanding these perceived boundaries helps identify potential resistance points or adoption barriers that might emerge during implementation, regardless of the eventual empirical effect size. Additionally, these bounds serve as a baseline for measuring how professional perspectives evolve as AI integration matures, providing insight into the gap between anticipated and realized impacts in accounting practice.

c. Methodology and Findings

The Current Status of AI Utilization in Accounting

To describe the use of generative AI in accounting, we survey accountants to ask about the integration of AI tools in their workflows, the frequency of their AI usage, and for which tasks. Table 3 reports the average survey responses. We find that 38% of accountants either partially or fully integrated ChatGPT and AI-powered accounting software into their workflows in November 2024. This finding indicates the rapid adoption of AI tools in accounting given that Humlum and Vestergaard (2024) finds that only 23% of accountants use ChatGPT in their work in late 2023 and

early 2024. In our survey, the median accountant uses generative AI tools occasionally (1-2 days a week) and for specific tasks in their workflow. Less than 10 percent of accountants never use generative AI in their work. Meanwhile, the top 10 percent of accountants report using generative AI numerous times per day and that it is a core part of daily work. This suggests that generative AI is an important tool for some accountants, but that there is heterogeneity among accountants in the use of generative AI.

We also survey accountants about their perception of the value of generative AI. Similar to the heterogeneity in Generative AI usage, we find differing opinions about its (net) value. Table 4 indicates three important areas in the benefits and costs of Generative AI in accounting: time, application, and accuracy. In Table 5, we consider three dimensions of value: time savings, breadth of application, and accuracy. For time savings, we find that on one end, 21 percent of accountants believe there are no time savings from the use of generative AI. On the other end, 26 percent of accountants believe there are moderate time savings, where Generative AI can reduce the time to complete tasks by 21 to 40 percent. Few accountants report beliefs that Generative AI can reduce time savings substantially (more than 40 percent).[3]

For breadth of application, we ask accountants about the fraction of routine tasks that are likely to be handled by generative AI. The median response is that 21 to 40 percent of routine tasks are likely to be handled to generative AI, but 19 percent of accountants reported 0 to 20 percent and 12 percent reported 61 to 80 percent. We find similar disagreement about the ability of generative AI to classify transactions without human review: the median accountant expects 21 to 40 percent of transactions can be AI classified, but the 23 percent of accountants believe only 0 to 20 percent

[3] One concern regarding Generative AI is career concerns by accountants in the pre-assessment survey. Interestingly, our untabulated post-survey responses indicate that job satisfaction regarding (accountant) career due to Generative AI is still positive. One interpretation is that the integration of Generative AI into their work may make their jobs more interesting and them prepared for the digital economy (Choi et al., 2024).

can be AI classified, and 12 percent of accountants reported 61 to 80 percent. This suggests that the median accountant believes that Generative AI can be widely helpful for routine tasks and the classification of transactions, but that there is also disagreement about the extent of its usefulness. In terms of accuracy, we find that accountants believe that Generative AI may substantially decrease the number of accounting errors. The median response is that generative AI is expected to decrease errors by 21 to 40 percent, but there is substantial dispersion where 34 percent of accountants reporting less than 20 percent and 12 percent of accountants reporting more than 60 percent. Although the overwhelming majority of accountants report that Generative AI is likely to decrease accounting errors, there is significant disagreement about the amount of error reduction.

We ask accountants about how they use Generative AI for different accounting tasks. These tasks include data entry, financial reporting, learning & training, financial analysis, business communication, quality assurance, administrative work, and advisory services. Each task is defined in Appendix A. Table 3 shows the fraction of accountants that use Generative AI for each task. Data entry involves the most use of Generative AI, where 44 percent of surveyed accountants report using generative AI. Tasks that feature writing, such as business communication and administrative work, also feature heavy use of generative AI, 43 and 44 percent respectively. Tasks that require human expertise, such as advisory services and quality assurance, tend to use less Generative AI, where only 15 and 27 percent of accountant report using Generative AI, respectively. These unconditional associations are suggestive that AI is most helpful for simpler tasks and tasks that involve writing.

These survey result show that within our sample of accountants, there is generally widespread use of Generative AI for a broad range of accounting tasks and a positive view of the value of Generative AI in terms of productivity, breadth of applicability, and quality. However, there is

dispersion in the extent to which accountants believe generative AI to be helpful. This dispersion is helpful for our following empirical tests where we document how generative AI changes labor allocation, labor productivity, reporting quality, and how generative AI interacts with human capital.

Generative AI and Accountant Productivity

In this subsection, we study the extent to which generative AI improves accountant productivity. To empirically measure productivity gains or losses and compare them against reported beliefs about productivity gains or losses, we estimate the following Poisson regression:

$$\log\left(E[\text{Productivity}_{i,t}|UsageofAIinFR_{i,t}, X_{i,t}]\right) = \delta_t + \beta\, UsageofAIinFR_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

where $\text{Productivity}_{i,t}$ is the productivity of accountant i for survey time t, where we measure productivity as the number of clients, billable hours, and non-billable hours. $UsageofAIinFR_{i,t}$ is an indicator variable equal to 1 if the accountant uses Generative AI and 0 otherwise. We report the average effects for all coefficients. Our null hypothesis is that Generative AI usage is not associated with a difference in accountant productivity, conditional on accountant characteristics ($X_{i,t}$).

Table 6 shows that accountant AI usage is associated with greater productivity: having more clients and more billable hours. Our surveyed accountants have on average 6 clients to support in a week and accountants that use Generative AI have 66 percent more clients to support in a week. These finding contrasts that of no significant increase in total clients, in Column (1). Taken together, these results suggest that accountants are supporting existing clients better in the early stages of adopting Generative AI. In addition to having more clients to support simultaneously, accountants that use Generative AI also report 12 percent billable hours. We find no significant association between Generative AI usage and non-billable hours although the coefficient is negative. These

findings suggest that conditional on accountant characteristics, using Generative AI is associated with greater productivity, while point out the possibility of switching from non-billable hours to billable hours (Baudot et al., 2022).

These findings corroborate the surveyed perceptions of accountants about the value of Generative AI. In Table 5, we show that our sample of accountants believe generative AI decreases the time to complete tasks by on average 32 percent. This is within the range of estimates of productivity gains (12 to 66 percent) for accountants that use generative AI versus those that do not. Therefore, the magnitudes of our estimated productivity gains are comparable to that of the perceived productivity gains reported by accountants.

We can put this result in the context of the prior literature. Although the literature has documented productivity gains associated with Generative AI, prior studies often use experimental settings (e.g., Noy and Zhang, 2023). As one of a few exceptions, Brynjolfsson et al. (2024) show that Generative AI improves the productivity of customer support agents by decreasing the time to resolve issues by on average 15 percent. However, similar to our motivating evidence in the previous subsection, there is substantial heterogeneity in the productivity gains associated with Generative AI. We show that surveyed accountants report that they use Generative AI and that they believe that it is helpful for their productivity in general, but the disagree about the extent of its helpfulness.

Generative AI Changing Accountant Time Allocation

We empirically examine how Generative AI changes the allocation of time across accounting tasks within an accountant. We estimate the association between accountant generative AI usage and their time allocation across tasks, conditional on measures of experience. We estimate the following OLS regression for each task:

$$Task_{i,t} = \delta_t + \beta UsageofAIinFR_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

where $Task_{i,t}$ is the percentage points of time by accountant i spent on one of the following aforementioned accounting tasks for survey time t, δ_t is a survey time fixed effect, $UsageofAIinFR_{i,t}$ is an indicator variable equal to 1 if the accountant uses Generative AI and 0 otherwise, $X_{i,t}$ are accountant-specific control variables, such as whether they have a CPA, level of education, and years of experience. The coefficient of interest is β, where our null hypothesis is that generative AI usage is not associated with accounting task time allocation, conditional on accountant characteristics.

Table 7 shows how accountant AI usage is associated with more time spent on business communications and quality assurance, and less on data entry, financial reporting and financial analyses. There are at least two effects of Generative AI usage on the allocation of accountant time. First, Generative AI may decrease the time it takes to complete tasks. For example, when Generative AI speeds up data entry, accountants complete this task faster and therefore it takes less of their time. Table 7 shows that accountants who use generative AI spend 8.3 percent less time on data entry. This is consistent with prior evidence in Table 5 documenting that 44 percent of accountant use generative AI for data entry. However, there is a counteracting secondary effect, which is that efficiency gains from Generative AI may increase the number of such tasks that an accountant does. This secondary effect can explain why Generative AI is commonly used in business communication, but time spent on this increases with AI usage. Table 7 shows that accountants who use AI spend 6.5 percent more of their time on business communication. Furthermore, we find a negative association between Generative AI usage and financial reporting, financial analysis, and a positive association with quality assurance and administrative work. The quality assurance finding suggests a human-interaction channel through which financial reporting quality can be improved. These findings complement prior studies, which don't indicate which

activities Generative AI users use their saved time for (e.g., DellAcqua et al., 2024). Our findings also collaborate with Eisfeldt et al. (2024), which explain how Generative AI is more helpful for financial lending tasks that involve communicating with borrowers, analyzing financial data, and computing payment schedules, but Generative AI is less helpful for more complex tasks such as approving loans and human interactions with borrowers.

An important control variable is accountant characteristics because these characteristics are likely to be related to both tasks and AI usage. Accountants without a CPA certification are likely to be younger and more versed in modern generative AI tools, but they are also more likely to do less complex tasks, such as data entry. The untabulated results indicate this association between CPA certification and task. CPA certified accountants are significantly less likely to spend time on simple tasks and are more likely to spend time on complex tasks. On average, CPA certified accountants spend 9.2 percent less of their time on data entry, but they spend 4.4 percent more of their time on business communication and 2.5 percent more on quality assurance. In terms of time, for a 40-hour work week, a 9 percent reallocation of time corresponds to 3.6 hours. This implies that accountant experience is an important omitted variable in the unconditional associations that we document in Table 7. At least, we control for CPA to mitigate this concern. CPA certified accountants may be less likely to be familiar with generative AI and also more likely to perform complex tasks, which would bias the estimated effect of AI usage on time allocation.

In sum, we show that generative AI is an important tool that is frequently used by some accountants and that its use is associated with productivity improvement while spending less time on data entry, financial reporting and financial analysis (, which account for 50% of survey participants' time on average), but more time on business communication, quality assurance and administrative work. So far in our analysis, we have compared the relative productivity and allocation of time of an

accountant with their use of generative AI. In the following subsection, we explore whether these accounting labor practices change with the benefit of or at the cost of financial reporting quality.

Generative AI and Financial Reporting Quality

A potential concern with Generative AI increasing the number of clients and billable hours for an accountant is that quality may suffer. Survey evidence in Table 5 and described in the previous subsection suggests that accountants believe that Generative AI may increase accounting accuracy by catching errors with a meaningful number of skeptics (e.g., None or Negative). To empirically test this association, we estimate whether earnings persistency increases with the use of Generative AI. High quality earnings are more persistent than low quality earnings (Dechow et al., 2010), especially when measured at the monthly frequency. We estimate the following OLS regression:

$$\text{Earnings}_{c,i,t} = \beta_0\, Post\ AI_{i,t} + \beta_1 \text{Earnings}_{c,i,t-1} + \gamma\, Post\ AI_{i,t} \times \text{Earnings}_{c,i,t-1} + \epsilon_{c,i,t}$$

where $\text{Earnings}_{c,i,t}$ is the earnings of client firm c that are audited by accountant i and for month t, and $\text{Earnings}_{c,i,t-1}$ is the 1-month lagged earnings, and $Post\ AI_{i,t}$ is an indicator variable whether the accountant uses Generative AI.

Table 8 shows that earnings persistence increases after the implementation of Generative AI. Prior to the implementation of Generative AI, earnings has a monthly persistence of 0.77, which increases by 15 percentage points with the use of Generative AI. Before these clients use Generative AI-powered accounting software, the Partner Firm's system, all of these clients and their accountants have used QuickBooks, which provides rule-based categorization. This suggests that Generative AI, relative to basic accounting software without AI tools, may decrease errors and noise in earnings, resulting in more persistent earnings that better captures the economic state of the firm although it is difficult to rule out the explanation of these treated clients' fundamental changes around the time of adopting Generative AI-powered accounting software.

In addition to more persistent earnings, we find that Generative AI improves the informativeness and timeliness of monthly financial reporting. Firms where accountants use Generative AI have more granular reporting of transactions by account type. For example, these account types include expenses, assets, and liabilities. The average firm has 4.8 account types and Table 8 shows that firms where accountants use Generative AI on average have an additional 1.3 unique accounts, which is an increase of 26 percent. These estimates are robust to the inclusion of firm and time fixed effects. Therefore, the usage of Generative AI in financial reporting is associated with more granular transaction account reporting, which can be a feature of higher quality monthly financial reporting.

Furthermore, accountants that use Generative AI on average close the books faster than accountants that do not. On average, for each month, accountants require about 2 weeks to close the books for the previous month. Table 4 documents that accountants that use generative AI on average close the books 4.2 days faster, which is an improvement of about 30 percent. This finding is also robust to including firm and time fixed effects.

Overall, we show that accountants who use Generative AI report more persistent earnings and more granular transaction and close the books faster than accountants who do not use Generative AI but still use basic accounting software. These findings are not driven by time-invariant differences across firms or common time series variation in macroeconomic conditions. This suggests that the usage of Generative AI is associated with improving monthly financial reporting quality.

Interaction between Generative AI and Accountant Human Capital

We have shown that generative AI is helpful for simple accounting tasks, such as data entry, but also for more complex tasks that include writing such as business communication and quality

assurance. This raises the question as to whether Generative AI is most complementary to experienced or inexperienced accountants or both. The literature has explored this question about the interaction of AI and human capital in financial settings, such as Costello et al. (2020). We conduct a similar exercise in the setting of financial bookkeeping.

To evaluate how the usage of Generative AI relates to human capital, we empirically estimate whether accountant characteristics can explain the propensity to use Generative AI tools. We estimate the following OLS regression:

$$\text{AI Utilization}_{c,i,t} = \gamma X_{c,i,t} + \epsilon_{c,i,t}$$

where $\text{AI Utilization}_{c,i,t}$ measure the degree to which accountant i uses Generative AI in month t for client c, and $X_{c,i,t}$ is the experience of the accountant and whether the accountant is CPA certified.

Table 9 shows that more experienced accountants tend to utilize Generative AI tools more for simple tasks, such as transaction characterization, but less for complex tasks such as accounting for accruals. A 1 standard deviation increase in accounting experience (i.e., 2 among sample accountants in Table 9) is associated with a 6 percent increase in the utilization of AI in transaction categorization and a 3 percent decrease in its use for accruals. We find marginally negative evidence of CPA certification and the utilization of generative AI. This suggests a nuanced relationship between accountant expertise and AI utilization, where accountant experience is associated with using Generative AI for simpler tasks (e.g., invoice and receipt matching). More generally, this also suggests that experienced and inexperienced accountants similarly utilize generative AI.

To more formally test this interpretation, we estimate by OLS:

$$\text{AI Utilization}_{c,i,t} = \beta\tau + \gamma\tau \times X_{c,i,t} + \epsilon_{c,i,t}$$

where we estimate the trend to AI Utilization$_{c,i,t}$ and how this trend differs depending on accountant experience and CPA certification. In Table 10, we find that there is a strong positive trend to AI utilization: τ is the number of months since January 2023, and the positive and significant coefficient β indicates that utilization of AI in accruals accounting has increased over time. There are two possible interpretations of this results. First, the Partner Firm's workflow has improved overtime and led to higher utilization. Alternatively, the reinforcement learning feature of AI tools has learned from the human usage and improved (Bai et al, 2022). We find small effects of the interaction between experience and CPA on this time trend to AI utilization, suggesting that AI utilization has been helpful for both experienced and inexperienced accountants.

These results are highly relevant to recent debates on whether Generative AI may be replacing the need for inexperienced accountants. Our findings indicate that there is a nuanced relationship between the usefulness of Generative AI and accounting human capital.

5. Concluding Remarks

This study investigates the transformative potential of Generative AI in accounting, focusing on its impact on labor productivity and financial reporting outcomes. Our primary aim is to carefully describe *how* accountants are engaging with AI technology in their day-to-day work, and to what extent this engagement appears to affect labor dynamics as well as work outcomes. With AI rapidly evolving and increasingly becoming an integral part of the accounting workforce, we believe this early evidence provides a crucial basis for future academic discourse and empirical exploration in this domain.

We collaborated with an anonymous firm, a leading provider of AI technology for accountants, to gain proprietary access to both accounting professionals and the underlying systems. This unique partnership allowed us to "look under the hood" and understand how emerging AI technologies

reshaping accounting practices are. Leveraging granular field data, we quantitatively analyze Generative AI technologies in financial reporting and measure changes in financial reporting quality. To complement these findings, we also analyzed survey data from a panel of accountants across the U.S. This dual-pronged approach enables us to construct a comprehensive narrative about how AI adoption influences labor dynamics, task reallocation, and the quality of financial reporting.

We reiterate that there are important caveats to our descriptive study. First, the adoption of AI-powered accounting software may be endogenous, as firms and accountants who embrace this technology likely differ systematically from those who do not, complicating efforts to establish causal relationships. Second, while our proprietary data from multiple firms offers a unique advantage, the relatively small sample size may constrain the broader applicability of our findings. Third, as AI integration in financial reporting is still in its early stages, the long-term effects and potential unintended consequences remain unclear.

There are many facets of AI-accountant interactions, and testing these comprehensively lies beyond the scope of this study. As the integration of AI in the accounting profession continues to unfold, there is ample opportunity for future research to explore these dynamics more systematically. This paper provides a foundational understanding, offering key insights to guide those efforts. Ultimately, we emphasize that while Generative AI holds immense promise for accountants, its integration into accounting workflows encompasses many nuanced details and dimensions. By shedding light on these nuances, our study serves as an important first step in understanding the usage and effects of Generative AI in accounting.

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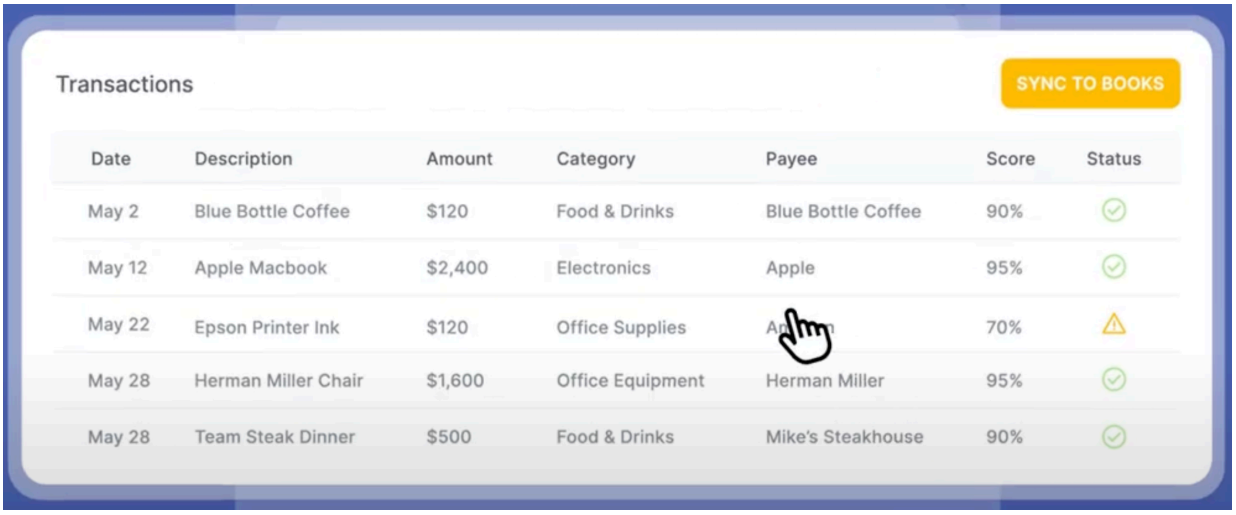
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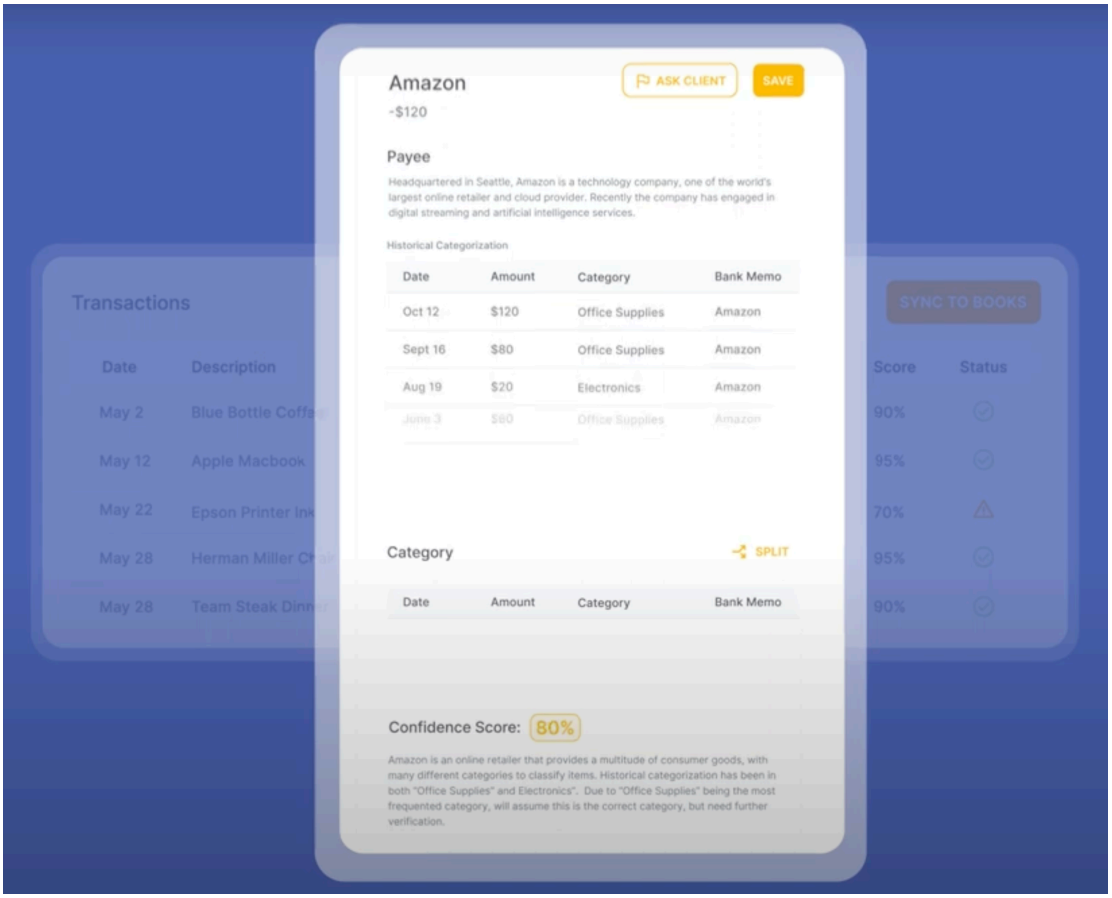
Figure 1: Examples of Auto-Categorization and Accrual Recognition

Panel A shows an example of a transaction categorization interface, where individual transactions are assigned to categories and payees are identified automatically by the software. Also, transactions include attributes such as date, description, amount, category, payee, and confidence score. For instance, "Epson Printer Ink" purchase is categorized under "Office Supplies" with confidence score of 70%. Confidence scores and statuses provide additional context for each categorization, helping identify which may require further attention. Panel B focuses on a detailed categorization breakdown for a specific payee, in this case, "Amazon". The interface highlights historical categorizations for Amazon transactions, which span multiple categories such as "Office Supplies" and "Electronics". A confidence score (e.g., 80%) is provided, and the system explains how it prioritizes frequently used categories, while flagging transactions that may need verification. This panel emphasizes transparency and historical context components in categorization. Panel C Accrual Recognition shows the accrual recognition interface, where recurring expenses are identified and categorized. The table shows key attributes such as payee, expense account, amount, status, accrue date, and action buttons for manual adjustments.

Panel A: Auto-Categorization Example (Part 1/2)



Panel B: Auto-Categorization Example (Part 2/2)



Panel C: Accrual Recognition

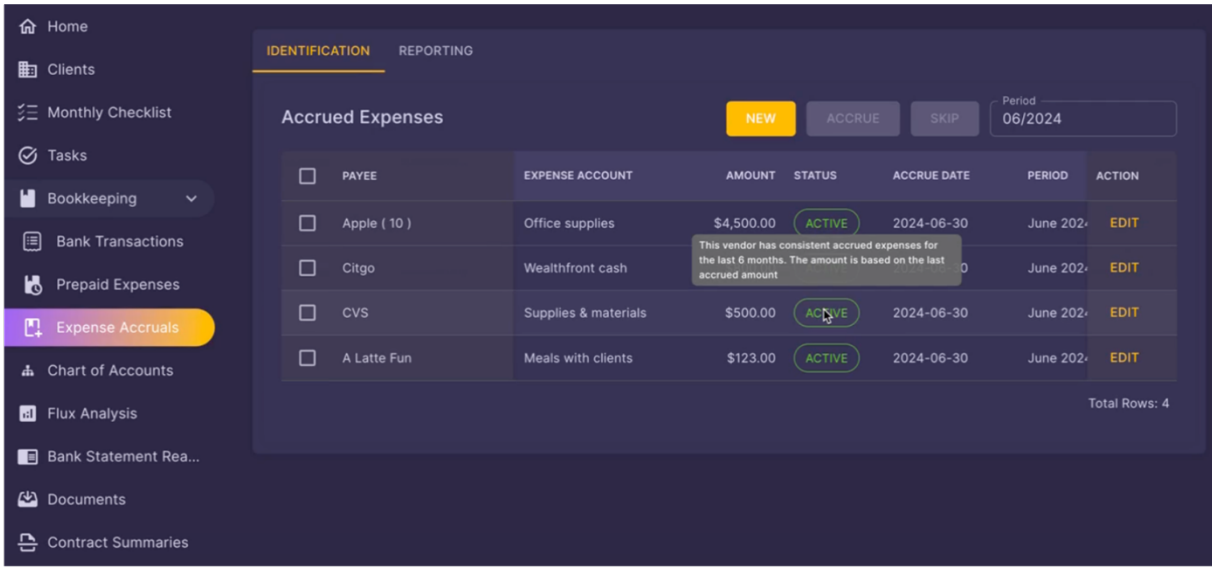


Figure 2: Categorized Transaction Ratios by Companies

This figure compares the ratio of correctly categorized transactions across four accounting software tools. The test set is comprised of 272 transactions, the same test set is used with each tool.

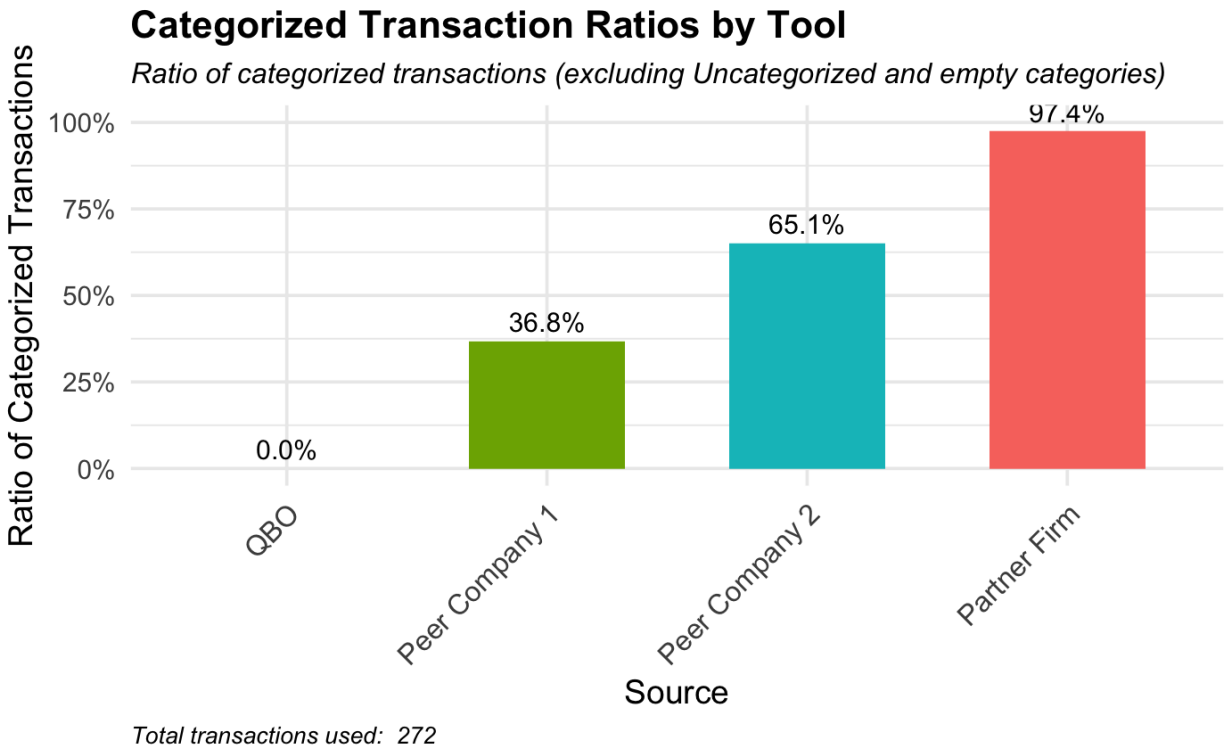


Figure 3: Partner Firm's Basic System Architecture

This figure illustrates the foundational components of the Partner Firm's system for handling accounting processes. The workflow consists of three main components. First, data injection, the system ingests raw data from various sources, including transactional data, financial records, client inputs, etc. to create a unified dataset for further processing down the line. Second, knowledge graph, ingested data is structured into a knowledge graph that captures relationships between entities (e.g., accounts, categories, transactions) to effectively organize data and process context-aware processing. Finally, the knowledge graph is utilized by a Large Language Model (LLM), which uses natural language processing to analyze, categorize, and interpret financial data for decision making and insights.



Figure 4: Data Source

This figure depicts the sources of data for our empirical analyses. Surveys are administered via Qualtrics, a survey platform. Accountants from three broad groups are responding to surveys: (1) 'internal accountants' from the Partner Firm, these accountants service external clients such as small and midsized businesses (SMBs) and startups, (2) 'external accountants' who work at accounting firms that license the Generative AI technology by the Partner Firm, these accountants service similar external clients such as small and midsized businesses (SMBs), (3) external accountants who have no affiliation with the Partner Firm. Field data is proprietary data provided by the Partner Firm. This granular data is at the accountant level (e.g. utilization), task level (e.g. expense categorization), and client level (e.g. monthly revenue and expense).

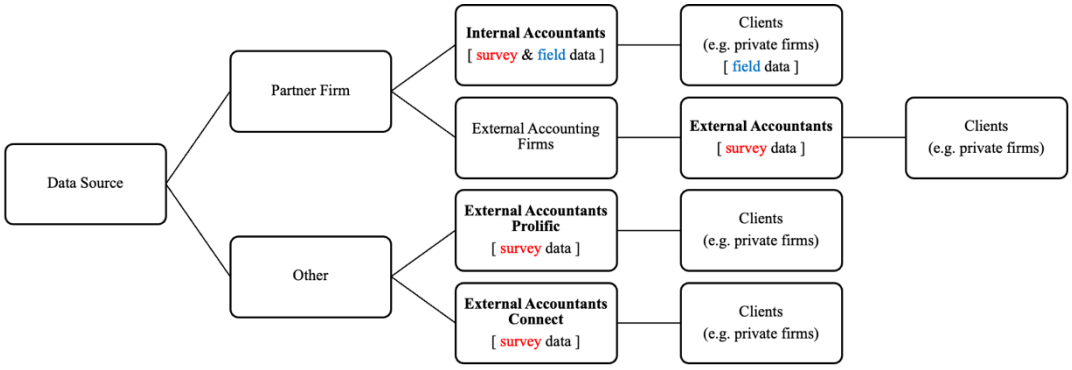


Table 1: Transaction Confidence Score Analysis

This table presents results from four OLS regressions that estimate the determinants of confidence scores in transaction categorization. The independent variables include whether the transaction was matched, length of the description, payee frequency, and expense classification. Fixed effects are incrementally added: account fixed effects are included in all regressions, while month, payee, and client fixed effects are added in iteratively for columns 2 to 4. Observations are at the transaction level, with standard errors clustered by client within parentheses. Appendix A describes variables.

	(1)	(2)	(3)	(4)
	Confidence Score	Confidence Score	Confidence Score	Confidence Score
Matched	0.107***	0.107***	0.138***	0.139***
	(0.006)	(0.008)	(0.010)	(0.010)
Length of Description	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000_	0.001
Payee Frequency	0.000	0.479***	0.523***	0.534***
	(0.000)	(0.112)	(0.109)	(0.118)
Expense	0.022	0.457***	0.342**	0.321*
	(0.115)	(0.156)	(0.152)	(0.163)
Unit	Transaction	Transaction	Transaction	Transaction
Observations	2,279	2,279	2,279	2,279
R-square	0.340	0.624	0.650	0.651
Account FE	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes
Payee FE	No	No	Yes	Yes
Client FE	No	No	No	Yes
Cluster	Client	Client	Client	Client

Table 2: Descriptive Statistics

This table presents descriptive statistics for our data. Panel A reports survey participant demographics and engagement metrics, including experience, education, number of clients served during a week, and weekly billable hours. Panel B reports financial reporting quality metrics, including the number of unique accounts used in reporting, average days to record transactions, and an indicator variable for Post AI (partner firm's software) adoption. These metrics measure timeliness, informativeness, and potential improvements in financial reporting processes associated with the use of Generative AI. Panel C highlights AI utilization metrics, including Auto-categorization (proportion of auto-approved or matched transactions), Software Utilization (ratio of synced to total ledger transactions), Accrued Expense Utilization (proportion of posted accrual journals to total suggested accruals), and Prepaid Expense Utilization (proportion of posted prepaid journals to total suggested entries). Panels D, E, and F show correlations among previously mentioned metrics. Appendix A describes variables.

Panel A: Survey (Tables 3-7)

	Number	Mean	Std	25%	50%	75%
Usage of Gen AI in FR	277	0.105	0.307	0.000	0.000	0.000
CPA	277	0.527	0.451	0.000	0.500	1.000
Education	277	16.159	1.531	16.000	16.000	18.000
Experience	277	9.513	8.738	1.000	7.000	15.000
Total Clients	277	50.805	112.851	5.000	14.000	45.000
Weekly Clients	627	7.443	8.902	3.000	5.000	9.000
Billable Hours	627	32.566	13.414	25.000	35.000	40.000
Non-billable Hours	627	9.658	10.492	2.000	6.000	14.000

Panel B: Financial Reporting Quality (Table 8)

	N	Mean	Std	25%	50%	75%
# of Unique Accounts	837	4.823	3.147	2.000	4.000	6.000
Avg Days to Record Transactions	1,033	12.560	16.814	-0.981	11.124	31.000
Post AI	1,033	0.558	0.497	0.000	1.000	1.000

Panel C: AI Utilization (Tables 9-10)

	Number	Mean	Std	25%	50%	75%
Auto-categorization	749	0.665	0.281	0.500	0.752	0.881
Software Utilization	352	0.789	0.346	0.595	0.953	1.000
Accrued Expense Utilization	511	0.337	0.454	0.000	0.000	1.000
Prepaid Expense Utilization	175	0.162	0.344	0.000	0.000	0.000

Panel D: Correlation Table for Tables 3-7

	(1)	(2)	(3)	(4)	(5)
(1) Usage of Gen AI in FR	1.000				
(2) CPA	0.229	1.000			
(3) Education	-0.066	0.267	1.000		
(4) Experience	-0.096	-0.095	0.039	1.000	
(5) Total Clients	-0.056	-0.049	0.024	0.084	1.000

Panel E: Correlation Table for Table 8

	(1)	(2)	(4)
(1) # of Unique Accounts	1.000		
(2) Avg Days to Record Transactions	-0.184	1.000	
(4) Post AI	0.010	-0.044	1.000

Panel F: Correlation Table for Tables 9-10

	(1)	(2)	(3)
(1) Auto-categorization	1.000		
(2) Software Utilization	0.141	1.000	
(3) Prepaid Expense Utilization	-0.116	0.790	1.000

Table 3: Patterns of AI Integration and Usage

This table presents survey responses from accountants regarding the integration, frequency of use, and application of Generative AI tools in their workflows. The table is divided into three panels, each addressing an aspect of AI adoption and usage. Panel A reports average responses about the integration of generative AI tools in accountant workflows. The majority indicated that they are occasionally used for specific tasks (26.35%), reflecting the exploratory stage of adoption for many accountants. Panel B examines the frequency of Generative AI usage in accountant tasks. Panel C highlights the primary application of Generative AI tools in accounting workflows. The most frequently reporting is data entry (44.40%) and administrative work (44.40%).

Panel A:

How integrated are Generative AI tools (e.g., ChatGPT and AI-Powered Accounting Software) in your workflow? (Select one answer)		
Answers	Count	Percentage
Occasional (specific tasks only)	73	26.35%
Partially integrated (regular but not essential use)	68	24.55%
Experimental (testing and evaluating)	63	22.74%
Fully integrated (core part of daily work)	37	13.36%
Not currently using	36	13.00%

Panel B:

How often do you currently use Generative AI tools in your workflow? (Select one answer)		
Answers	Count	Percentage
Occasionally (1-2 days a week)	68	24.55%
Rarely (a few times a month)	56	20.22%
Daily (a few times daily)	49	17.69%
Frequently (3-4 days a week)	48	17.33%
Numerous times daily	29	10.47%
Never	27	9.75%

Panel C:

How often do you currently use Generative AI tools in your workflow? (Select one answer)		
Answers	Count	Percentage
Data entry (entering and extracting data, matching invoices)	123	44.40%
Administrative work (documentation, compliance tasks)	123	44.40%
Business communication (client meetings, team coordination, project management)	118	42.60%
Financial analysis (reviewing data, auditing, performance measures)	111	40.07%
Learning and training (new skills, regulatory updates)	98	35.38%
Financial reporting (reconciliation, categorization, journaling)	85	30.69%
Quality assurance (checking accuracy of deliverables, internal reviews, error detection)	75	27.08%
Advisory service (business planning, tax support)	43	15.52%
Other (please specify): _____	25	9.03%

Table 4: Adoption of Generative AI in Financial Reporting

This table presents survey responses from 277 accountants regarding their usage, perceptions, and expectations of generative AI tools in financial reporting. The table is organized into three panels, each addressing distinct aspects of AI adoption, including primary concerns, anticipated benefits, and potential negative effects. Panel A summarizes respondents' primary concerns in their daily work. These include issues such as accuracy concerns (55.60%), time pressures (41.42%), and compliance requirements (28.52%). Other concerns include data security, quality control, repetitive tasks, and client relationships, and others are also represented but to a lesser extent. Panel B summarizes respondents anticipated potential benefits from using Generative AI tools to address their primary concerns. The most frequently reported answers were routine tasks (64.26%), faster completion of work and deadlines (58.48%), and improved accuracy (49.46%). Panel C examines potential negative impacts and concerns about Generative AI. The most frequent reported concerns include AI errors (62.09%), data security (43.32%), and job security (37.18%). Together these panels provide a comprehensive overview of the accountants' perspectives on adopting generative AI tools.

Panel A:

What are your primary concerns in your daily work as an accountant? (Select up to 3 choices) - Selected Choice		
Answer	Count	Percentage
Accuracy concerns (avoiding mistakes in calculations and reports)	154	55.60%
Time pressures (meeting deadlines, handling busy seasons)	115	41.52%
Compliance requirements (following accounting rules and standards)	79	28.52%
Work-life balance (managing overtime, work fatigue, setting boundaries)	78	28.16%
Data security concerns (protecting sensitive financial information)	74	26.71%
Quality control pressures (ensuring consistency across team outputs)	60	21.66%
Repetitive tasks (recurring, routine, mundane)	60	21.66%
Client relationships (responding to client needs)	59	21.30%
Professional growth (gaining certifications, advancing career)	46	16.61%
Resource limitations (managing with budget/tool constraints)	29	10.47%
Technology challenges (learning new software and tools)	28	10.11%
Internal communication (coordinating with colleagues)	26	9.39%
Other (please specify):	2	0.72%

Panel B:

What potential benefits do you anticipate from using Generative AI tools in your work to reduce the concerns you chose above? (Select up to 3 choices) - Selected Choice		
Answer	Count	Percentage
Automation of routine tasks	178	64.26%
Faster completion of work and deadlines	162	58.48%
Improved accuracy	137	49.46%
Improved work-life balance	55	19.86%
Consistent quality	48	17.33%
Better client service	41	14.80%
Better compliance management	40	14.44%
Easier technology adoption	34	12.27%
Optimized resource utilization	29	10.47%
Enhanced team communication	28	10.11%
Stronger data security	17	6.14%
Career advancement	13	4.69%
Other (please specify)	1	0.36%

Panel C:

What potential negative impacts/concerns do you expect from incorporating Generative AI tools into your workflow? (Please choose up to 3 concerns) - Selected Choice		
Answer	Count	Percentage
AI errors (mistakes in AI-generated outputs)	172	62.09%
Data security (sensitive information leakage and system failures)	120	43.32%
Job security (adapting to new roles)	103	37.18%
Technology dependence (reducing human judgment and practical skill development)	100	36.10%
Ethical issues (ensuring fair AI use)	78	28.16%
Review time (checking AI work for accuracy)	75	27.08%
Integration challenges (connecting AI tools with existing systems)	68	24.55%
Learning needs (time to learn and onboard new tools)	59	21.30%
Team interactions (changes in collaboration and knowledge sharing)	21	7.58%

Table 5: Expected AI Impact Assessment

This table summarizes survey responses on the anticipated impacts of AI-powered accounting tools across four key dimensions. Panel A reports expected reductions in task completion time, with a mean reduction of 32.65%. The largest group, 48.68%, anticipates moderate time savings (21-40%). Panel B highlights automation potential, with a mean of 39.15% of routine tasks expected to be handled by AI tools, 35.45% of respondents predict 21-40% automation. Panel C examines classification accuracy expectations, with a mean of 39.93%, and 31.75% of respondents expect 41-60% accuracy for transactions classified without human review. Panel D documents expected error reduction, with a mean of 34.78%. The most common expectation is a 21-40% reduction in errors, reported by 35.45% of respondents. These tables provide an overview of accountants' expectations regarding AI's ability to enhance efficiency, accuracy, and error reduction in accounting workflows.

Panel A:

What percentage reduction in task completion time do you expect with AI-assisted accounting software (e.g., Botkeeper, Vic.ai, and Truewind)? Example: A 20% reduction means a 5-hour task takes 4 hours; a 60% reduction means it takes 2 hours.
(Select one answer.)

Options	Count	Percentage
21-40%	92	48.68%
41-60%	50	26.46%
0-20%	39	20.63%
61-80%	5	2.65%
None or Negative	3	1.59%
81-100%	0	0.00%
Mean		32.65%

Panel B:

What percentage of routine tasks do you expect to be handled by AI-powered automation tools?
(Select one answer.)

Options	Count	Percentage
21-40%	67	35.45%
41-60%	56	29.63%
0-20%	35	18.52%
61-80%	25	13.23%
None or Negative	4	2.12%
81-100%	2	1.06%
Mean		39.15%

Panel C:

What percentage of transactions do you expect AI-assisted accounting software to classify without human review correctly? (Select one answer.)		
Options	Count	Percentage
41-60%	60	31.75%
21-40%	47	24.87%
0-20%	45	23.81%
61-80%	23	12.17%
None or Negative	9	4.76%
81-100%	5	2.65%
Mean		39.93%

Panel D:

What percentage of error reduction do you expect when using AI-assisted review and validation tools? (Select one answer.)		
Options	Count	Percentage
21-40%	67	35.45%
0-20%	54	28.57%
41-60%	36	19.05%
61-80%	17	8.99%
None or Negative	10	5.29%
81-100%	5	2.65%
Mean		34.78%

Table 6: Accounting Labor Productivity

This table presents the results from four Poisson regressions that document the association between labor productivity and the use of generative AI. We measure performance using the total number of clients managed (column 1), weekly number of clients served (column 2), billable hours (column 3), and non-billable hours (column 4). We control for accountant characteristics: CPA certification, education, and experience. Each observation is a surveyed accountant (weekly). Standard errors are robust and reported in parentheses. Appendix A describes variables.

	(1)	(2)	(3)	(4)
	Total Clients	Weekly Clients	Billable Hours	Non-billable Hours
Usage of AI in FR	-0.364	0.663***	0.122**	-0.109
	(0.436)	(0.176)	(0.055)	(0.154)
CPA	-0.195	0.039	0.109***	-0.193*
	(0.295)	(0.118)	(0.040)	(0.100)
Education	0.043	0.017	-0.011	0.038
	(0.114)	(0.038)	(0.012)	(0.033)
Experience	0.017	0.008	0.001	0.001
	(0.014)	(0.005)	(0.002)	(0.005)
Unit	Accountant	Accountant-Week	Accountant-Week	Accountant-Week
Observations	277	627	627	627
R-squared	0.023	0.036	0.014	0.014
Fixed Effects	No	Week	Week	Week
Cluster	Robust	Robust	Robust	Robust

Table 7: Accounting Labor Allocation

This table presents results from eight regressions examining labor allocation among accountants internal and external to the partner company, specifically focusing on how time is distributed across tasks. For each regression, we have the share of time spent on a task as the dependent variable. The explanatory variable of interest is an indicator variable whether the accountant uses Generative AI. Each observation is a surveyed accountant weekly. Standard errors are robust are reported in parentheses. Appendix A describes variables.

	(1)	(2)	(3)	(4)
	Data Entry	Financial Reporting	Financial Analysis	Business Communication
Usage of AI in FR	-0.083***	-0.050*	-0.046**	0.065***
	(0.023)	(0.027)	(0.023)	(0.015)
CPA	-0.061***	-0.020	0.033**	0.021**
	(0.014)	(0.018)	(0.016)	(0.010)
Education	-0.016***	0.006	-0.001	0.007***
	(0.005)	(0.004)	(0.005)	(0.002)
Experience	-0.002***	0.002*	0.001*	0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Unit	Accountant-Week	Accountant-Week	Accountant-Week	Accountant-Week
Observations	627	627	627	627
R-Squared	0.125	0.035	0.017	0.081
Fixed Effects	Week	Week	Week	Week
Cluster	Robust	Robust	Robust	Robust

Continued:

	(5)	(6)	(7)	(8)
	Quality Assurance	Administrative Work	Advisory Services	Learning & Training
Usage of AI in FR	0.042***	0.032***	0.021	0.018
	(0.013)	(0.010)	(0.016)	(0.020)
CPA	0.010	0.035***	0.004	-0.023**
	(0.009)	(0.007)	(0.011)	(0.012)
Education	0.006**	-0.001	0.002	-0.004
	(0.002)	(0.002)	(0.003)	(0.003)
Experience	0.000	0.000	-0.001	-0.000
	(0.001)	(0.000)	(0.001)	(0.001)
Unit	Accountant-Week	Accountant-Week	Accountant-Week	Accountant-Week
Observations	627	627	627	627
R-Squared	0.049	0.092	0.019	0.012
Fixed Effects	Week	Week	Week	Week
Cluster	Robust	Robust	Robust	Robust

Table 8: Financial Reporting Quality

This table present results from three OLS regressions that show the association between financial reporting quality and use of Generative AI. The dependent variables are earnings at time t (column 1), the number of unique accounts recorded within a client-month (column 2), and the average number of days to record a transaction from the end of the month (column 3). For column 1, the independent variables include lagged earnings, an interaction term between lagged earnings and post-adoption indicator for the partners company's software, and post-adoption indicator. For columns 2 and 3, the primary explanatory variable of interest is whether the accountant uses Generative AI. The unit of observation is at the client-month level. Standard errors are clustered at the client level, and there are client-month fixed effects for columns 2 and 3. Appendix A describes variables.

	(1)	(2)	(3)
	Earnings_t	# Unique Accounts	Average Days to Record Transactions
Earnings_t-1	0.763***		
	(0.097)		
Earnings_t-1 × Post AI in FR	0.156*		
	(0.090)		
Post AI in FR	0.018	1.253***	-4.186*
	(0.026)	(0.280)	(2.344)
Unit	Client-Month	Client-Month	Client-Month
Observations	925	837	1,033
R-square	0.653	0.878	0.605
FE	No	Client-Month	Client-Month
Cluster	Client	Client	Client

Table 9: AI Utilization and Accountant Characteristics

This table presents results from three OLS regressions that estimate the association between accountant characteristics and the use of generative AI. Column 1 examines overall accuracy, defined as the percentage of transactions that were either auto-approved or matched relative to total bank transactions, providing a measure of the software's ability to accurately categorize transactions. Column 2 focuses on software utilization, calculated as the ratio of bank transactions synced via the partner company's software to total ledger transactions, this offers insights into the platform's adoption and integration into accounting workflows. Column 3 assesses prepaid expenses utilization, measured as the proportion of amortization journal entries posted via the software compared to total amortization journals in the general ledger, reflecting the software's role in the management of prepaid expenses. The accountant characteristics include experience (measured in years) and CPA status. The unit of observation is at the client-month level and standard errors are clustered at the client level. Appendix A describes variables.

	(1)	(2)	(3)
	Auto-Categorization	Software Utilization	Accrual Utilization
	Overall Accuracy	Utilization (Bank Transaction)	Prepaid Expenses Utilization
Experience	0.032**	0.024***	-0.015**
	(0.011)	(0.004)	(0.006)
CPA	-0.073*	-0.032	-0.029
	(0.035)	(0.048)	(0.057)
Unit	Client-Month	Client-Month	Client-Month
Observations	749	352	511
R-Squared	0.084	0.191	0.578
Cluster	Account	Account	Account

Table 10: AI Utilization over Time

This table estimates the effect of experience on the trend of Generative AI adoption. The dependent variables include prepaid expense utilization (columns 1 and 3) and accrued expense utilization (columns 2 and 4), measured as the proportion of posted entries relative to total entries for prepaid and accrued expenses. We estimate the time trend to Generative AI adoption (t) and how this trend differs depending on accountant experience and CPA certification. There are client fixed effects and standard errors are clustered by accountant. Appendix A describes variables.

	(1) Prepaid Expense Utilization	(2) Accrued Expense Utilization	(3) Prepaid Expense Utilization	(3) Accrued Expense Utilization
τ	0.045***	0.045**	0.068***	0.060***
	(0.005)	(0.014)	(0.012)	(0.012)
$\tau \times$ *Experience*			-0.002**	-0.004
			(0.001)	(0.002)
$\tau \times$ *CPA*			-0.003	0.024
			(0.008)	(0.029)
Unit	Client-Month	Client-Month	Client-Month	Client-Month
Observations	511	175	511	175
R-square	0.604	0.517	0.613	0.523
FE	Client	Client	Client	Client
Cluster	Accountant	Accountant	Accountant	Accountant

Appendix A. Variable Definitions

#	Variable Name	Explanation	Source	Unit
1	*Usage of Gen AI in FR*	Mapping of survey answers to numerical values: 'Never': 0, 'Rarely (a few times a month)': .2, 'Occasionally (1-2 days a week)': .4, 'Frequently (3-4 days a week)': .6, 'Daily (a few times daily)': .8, 'Numerous times daily': 1	Pre-Survey	Accountant
2	*CPA*	Mapping no, in progress/pursuing, yes to 0, 0.5, 1 respectively.	Pre-Survey	Accountant
3	*Education*	Mapping of survey answers to numerical values: 'High school diploma': 12, "Associate's degree":14, "Bachelor's degree": 16, "Master's degree": 18, "PhD or equivalent": 21	Pre-Survey	Accountant
4	*Experience*	Mapping of survey answers to numerical values: "<1 year": 0, "1-3 years": 1.5, "4-10 years": 7, "11-20 years": 15.5, "20+ years": 30	Pre-Survey	Accountant
5	*Total Clients*	Number of total clients indicated in pre-survey response	Pre-Survey	Accountant
6	*Weekly Clients*	Number of clients an accountant worked on during a given week, per weekly survey response to Q1	Weekly Survey	Accountant-Week
7	*Billable Hours*	Number of billable hours reported by an accountant on during a given week, per weekly survey response to Q2	Weekly Survey	Accountant-Week
8	*Non-billable Hours*	Number of non-billable hours reported by an accountant on during a given week, per weekly survey response to Q3	Weekly Survey	Accountant-Week
9	*Data Entry*	Reported as an integer during weekly survey. Including other responses to this question (lines 11 through 18), must sum to 100.	Weekly Survey	Accountant-Week
10	*Financial Reporting*	Reported as an integer during weekly survey. Including other responses to this question (lines 11 through 18), must sum to 100.	Weekly Survey	Accountant-Week
11	*Financial Analysis*	Reported as an integer during weekly survey. Including other responses to this question (lines 11 through 18), must sum to 100.	Weekly Survey	Accountant-Week
12	*Business Communication*	Reported as an integer during weekly survey. Including other responses to this question (lines 11 through 18), must sum to 100.	Weekly Survey	Accountant-Week
13	*Quality Assurance*	Reported as an integer during weekly survey. Including other responses to this question (lines 11 through 18), must sum to 100.	Weekly Survey	Accountant-Week

14	*Administrative Work*	Reported as an integer during weekly survey. Including other responses to this question (lines 11 through 18), must sum to 100.	Weekly Survey	Accountant-Week
15	*Advisory Services*	Reported as an integer during weekly survey. Including other responses to this question (lines 11 through 18), must sum to 100.	Weekly Survey	Accountant-Week
16	*Learning & Training*	Reported as an integer during weekly survey. Including other responses to this question (lines 11 through 18), must sum to 100.	Weekly Survey	Accountant-Week
17	*Earnings_t*	Accounting period's net income via income statement line item scaled by total assets.	Income Sheet	Client-Month
18	*Earnings_t-1*	This variable is the same as Earnings_t but lagged (1 month prior). Accounting period's net income via income statement line item but 1 month prior.	Income Sheet	Client-Month
19	*Earnings_t-1 * Post AI in FR*	Earnings_t-1' interacted with 'Post AI' indicator variable.	Income Sheet	Client-Month
20	*# of Unique Accounts*	Count of the number of distinct accounts used in the general ledger for a specific client during the reporting period.	General Ledger	Client-Month
21	*Avg Days to Record Transactions*	For a specific client during a specific reporting period (month), calculate the difference between the month end date and each transaction creation date, then average. If the difference is larger than 31, the difference is assigned as 31.	General Ledger	Client-Month
22	*Post AI in FR*	Indicator variable is equal to 1 beginning on and following 'start of engagement' date with partner company, 0 otherwise.	Partner Company Records	Client-Month
23	*Overall Accuracy*	Decimal value 0 to 1 via bank transaction data at client month level. Can be calculated as the: (number of auto-approved + matched) / (total bank transactions).	Bank Transaction Data	Client-month
24	*Utilization (Bank Transaction)*	Also, referred to as Software Utilization. This utilization calculation is referencing bank transactions. Decimal value 0 to 1 via bank transaction data at client month level. Can be calculated as the number of transactions synced from the Partner Firm to the books divided by the total number of ledger transactions. In other words, transactions on the books that are from the AI system divided by total number of all transactions on the books.	Bank Transaction Data	Client-month
25	*Prepaid Expenses Utilization*	Also, referred to as Accrual Utilization. Decimal value 0 to 1 via prepaid expenses data at client month level. Can be calculated as number of transactions TW posts amortization journal entries divided by total number of amortization journal entries. In other words those by (# by the AI system) / (# by the AI system + # not by the AI system).	Prepaid Expense Data	Client-month
26	*Accrued Expense Utilization*	Decimal value 0 to 1 via accrued expenses data at client month level. Although provided, this metric can be calculated as number of posted	Accrued Expense Data	Client-month

		journals divided by total number of accrued journals (both numbers are only considering activity that relates to accrued expense / the AI system module).		
27	τ	Maps month-year to integer values, January 2023 being 0 and December 2024 being 23.	Partner Company Records	Month
28	τ * *Experience*	Interaction of 't' and 'Experience'. This variable is constructed for partner company's internal accountants.	Pre-Survey	Accountant-Month
29	τ * *CPA*	Interaction of 't' and 'CPA'. This variable is constructed for partner company's internal accountants.	Pre-Survey	Accountant-Month

Appendix B. Survey Instrument

Pre-Survey (November 1, 2024)

We care about the quality of our survey data. For us to get the most accurate measures of your opinions, it is important that you provide thoughtful answers to each question in this study. Do you commit to providing thoughtful answers to the questions in this survey?

a) I can't promise either way.
b) Yes, I will.
c) No, I will not.

I. AI Usage and Experience:

1. How integrated are Generative AI tools (e.g., ChatGPT and AI-Powered Accounting Software) in your workflow?
    a) Fully integrated (core part of daily work)
    b) Partially integrated (regular but not essential use)
    c) Experimental (testing and evaluating)
    d) Occasional (specific tasks only)
    e) Not currently using

2. How often do you currently use Generative AI in your workflow?
    a) Numerous times daily
    b) Daily (a few times daily)
    c) Frequently (3-4 days a week)
    d) Occasionally (1-2 days a week)
    e) Rarely (a few times a month)
    f) Never

3. Which tasks do you currently use Generative AI? (Select all that apply)
    a) Data Entry (entering and extracting data, matching invoices)
    b) Financial Reporting (reconciliation, categorization, journaling)
    c) Financial Analysis (reviewing data, auditing, performance measures)
    d) Advisory Service (business planning, tax support)
    e) Quality Assurance (checking accuracy of deliverables, internal reviews, error detection)
    f) Learning and Training (new skills, regulatory updates)
    g) Business Communication (client meetings, team coordination, project management)
    h) Administrative Work (documentation, compliance tasks)
    i) Other (please specify): _____

4. How comfortable are you with learning new technologies?
    1 = Very uncomfortable
    2 = Somewhat uncomfortable
    3 = Neutral

4 = Somewhat comfortable
5 = Very comfortable

II. Perception and Plan

5. What is your general perception of Generative AI's impact on the accounting industry?
    a) Significant and positive
    b) Mild and positive
    c) Negligible impact
    d) Mild and negative
    e) Significant and negative

6. What are your primary concerns in your daily work as an accountant? (Choose up to 3 concerns)
    ___ Time pressures (meeting deadlines, handling busy seasons)
    ___ Repetitive tasks (recurring, routine, mundane)
    ___ Accuracy concerns (avoiding mistakes in calculations and reports)
    ___ Compliance requirements (following accounting rules and standards)
    ___ Technology challenges (learning new software and tools)
    ___ Professional growth (gaining certifications, advancing career)
    ___ Internal communication (coordinating with colleagues)
    ___ Client relationships (responding to client needs)
    ___ Work-life balance (managing overtime, work fatigue, setting boundaries)
    ___ Data security concerns (protecting sensitive financial information)
    ___ Quality control pressures (ensuring consistency across team outputs)
    ___ Resource limitations (managing with budget/tool constraints)
    ___ Other (please specify): _____

7. What potential benefits do you anticipate from using Generative AI tools in your work to reduce the following concerns? (Please choose up to 3 concerns)
    ___ Faster completion of work and deadlines
    ___ Automation of routine tasks
    ___ Improved accuracy
    ___ Better compliance management
    ___ Easier technology adoption
    ___ Career advancement
    ___ Enhanced team communication
    ___ Better client service
    ___ Improved work-life balance
    ___ Stronger data security
    ___ Consistent quality
    ___ Optimized resource utilization
    ___ Other (please specify): _____

1. What potential negative impacts/concerns do you expect from incorporating Generative AI tools into your workflow? (Please choose up to 3 concerns)
    ___ AI errors (mistakes in AI-generated outputs)
    ___ Review time (checking AI work for accuracy)
    ___ Data security (sensitive information leakage and system failures)
    ___ Technology dependence (reducing human judgment and practical skill development)
    ___ Job security (adapting to new roles)
    ___ Ethical issues (ensuring fair AI use)
    ___ Team interactions (changes in collaboration and knowledge sharing)
    ___ Learning needs (time to learn and onboard new tools)
    ___ Integration challenges (connecting AI tools with existing systems)
    ___ Other (please specify): _____

II. Demographics:

1. What is your highest level of education?
    a) High school diploma
    b) Associate's degree
    c) Bachelor's degree
    d) Master's degree
    e) PhD or equivalent
    f) Other (please specify): _____

    1b. If you answered b-e for question 1, please specify your major(s) _____: (Please type answer)

2. Do you have a CPA certification?
    a) Yes
    b) No
    c) In progress/pursuing CPA

3. How many years of ***accounting*** work experience do you have?
    a) Less than one year
    b) 1-3 years
    c) 4-10 years
    d) 11-20 years
    e) 20+ years

4. What is your gender?
    a) Male
    b) Female
    c) Non-binary
    d) Prefer not to say
    e) Other (please specify): _____

5. What is your age range?
    a) Under 18
    b) 18-24 years old
    c) 25-35 years old
    d) 36-50 years old
    e) 51-65 years old
    f) 65+ years old

III. Professional Context:

1. What is your current role or level in accounting? (Select one answer)
    a) Staff (Handles general accounting tasks like financial reporting, compliance, and account reconciliations) (1)
    b) Junior (Entry-level roles, focusing on bookkeeping, data entry, reconciliations) (2)
    c) Senior (More complex accounting tasks such as financial analysis, month-end close, and managing junior staff) (3)
    d) Manager (Oversees accounting teams, ensures compliance, handles complex reporting, budgeting, and forecasting) (4)
    e) Director/Partner (Drives firm-wide strategies, manages key client relationships, and participates in firm governance) (5)
    f) Other (please specify): (6) _____

3. What is your current firm's size?
    a) Small (1-10 employees)
    b) Medium (11-50 employees)
    c) Large (51-200 employees)
    d) Very Large (200+ employees)

2. How many (external) clients do you have in total under your account? (Enter numeric answer below): _____

4. What industries make up the majority of your client portfolio? (Select up to 3 industries)

    1) Agriculture, Forestry, and Fishing (SIC 01-09)
    2) Mining and Quarrying (SIC 10-14)
    3) Construction (SIC 15-17)
    4) Manufacturing (SIC 20-39)
    5) Transportation and Public Utilities (SIC 40-49)
    6) Wholesale Trade (SIC 50-51)
    7) Retail Trade (SIC 52-59)
    8) Finance, Insurance, and Real Estate (SIC 60-67)
    9) Services (Professional, Scientific, Technical, and Others) (SIC 70-89)
    10) Public Administration (SIC 91-97)
    11) Healthcare and Social Assistance (SIC 80)

12) Educational Services (SIC 82)
13) Information (Publishing, Telecommunications) (SIC 73)
14) Real Estate and Rental Leasing (SIC 65)
15) Utilities (SIC 49)

Weekly Survey (November 8, 2024; November 15, 2024; November 22, 2024)

We care about the quality of our survey data. For us to get the most accurate measures of your opinions, it is important that you provide thoughtful answers to each question in this study. Do you commit to providing thoughtful answers to the questions in this survey?

a) I can't promise either way.
b) Yes, I will.
c) No, I will not.

Client Base

1. How many clients did you work with this week?
(Please enter number of clients): _____

2. How many billable hours did you work this week?
(Please enter number of hours): _____

3. How many non-billable hours did you work this week?
(Please enter number of hours): _____

Time Allocation

4. How did you allocate your time across the following tasks this week? Please enter the percentage spent on each task category (The "*Total*" should add up to 100%)

a. Data Entry (entering and extracting data, matching invoices) _____
(1)
b. Financial Reporting (reconciliation, categorization, journaling) _. _____
(2)
c. Financial Analysis (reviewing data, auditing, performance measures) _____
(3)
d. Advisory Service (business planning, tax support) _____
(4)
e. Quality Assurance
(checking accuracy of deliverables, internal reviews, error detection) _____
(5)
f. Learning and Training (new skills, regulatory updates) _____
(6)
g. Business Communication
(client meetings, team coordination, project management) _____
(7)
h. Administrative Work (documentation, compliance tasks) _____
(8)
i. Other (please specify): _____
(9)

Total: _____

5. Which accounting software(s) and/or AI tool(s) did you use this week?
(Please select up to 3 tools you used most frequently this week)

- ☐ Quickbooks (1)
- ☐ Xero (2)
- ☐ Sage (3)
- ☐ NetSuite (4)
- ☐ Freshbooks (5)
- ☐ Vic.ai (7)
- ☐ Zeni (8)
- ☐ Docyt (9)
- ☐ TrueWind (12)
- ☐ Other (please specify) (11)

[Carry Forward Selected Choices - Entered Text from "Which accounting software(s) and/or AI tool(s) did you use this week? (Please select up to 3 tools you used most frequently this week)]

6. For the tools you selected in the previous questions, how helpful and effective were they for this week's tasks? (Please select one per row)

	Not helpful at all (1)	Slightly helpful (2)	Moderately helpful (3)	Very helpful (4)
Quickbooks (x1)	o	o	o	o
Xero (x2)	o	o	o	o
Sage (x3)	o	o	o	o
NetSuite (x4)	o	o	o	o
Freshbooks (x5)	o	o	o	o
Vic.ai (x6)	o	o	o	o
Zeni (x7)	o	o	o	o
Docyt (x8)	o	o	o	o

TrueWind (x9)	o	o	o	o
Other (please specify) (x10)	o	o	o	o

7. What tasks worked well with *[Tools selected from Q5., this question is asked once per tool (so if you choose 3 tools, it shows up 3 times]*? (Please enter your response below)

a) Data Entry and Extraction
b) Receipt and Invoice
c) Reconciliation and Categorization
d) Journaling and Financial Reporting
e) Financial Analysis and Auditing
f) Advisory Service (e.g., Business Planning and Tax)
g) Quality Assurance
h) Learning and Training
i) Business Communication
j) Administrative Work
k) Other (please specify)

8. Why did those tasks work well with *[Tools selected from Q5., this question is asked once per tool (so if you choose 3 tools, it shows up 3 times]* this week? (Please enter your response below)

9. What challenges or limitations did you encounter with *[Tools selected from Q5., this question is asked once per tool (so if you choose 3 tools, it shows up 3 times]* this week? (Please enter your response below)

a) Data Entry and Extraction
b) Receipt and Invoice
c) Reconciliation and Categorization
d) Journaling and Financial Reporting
e) Financial Analysis and Auditing
f) Advisory Service (e.g., Business Planning and Tax)
g) Quality Assurance
h) Learning and Training
i) Business Communication
j) Administrative Work
k) Other (please specify)

10. Why were those tasks challenging with *[Tools selected from Q5., this question is asked once per tool (so if you choose 3 tools, it shows up 3 times]* this week? (Please enter your response below)

Post-Survey (November 25, 2024)

We care about the quality of our survey data. For us to get the most accurate measures of your opinions, it is important that you provide thoughtful answers to each question in this study. Do you commit to providing thoughtful answers to the questions in this survey?

a) I can't promise either way.
b) Yes, I will.
c) No, I will not.

1. How often did you use Generative AI tools in your workflow during November 2024?
    a) Numerous times daily
    b) Daily (a few times daily)
    c) Frequently (3-4 days a week)
    d) Occasionally (1-2 days a week)
    e) Rarely (a few times a month)
    f) Never

2. What is your general perception of generative AI's impact on the accounting industry?
    a) Significant and positive
    b) Mild and positive
    c) Negligible impact
    d) Mild and negative
    e) Significant and negative

3. What are your primary concerns in your daily work as an accountant? (Please choose up to 3 concerns)
    ___ Time pressures (meeting deadlines, handling busy seasons)
    ___ Repetitive tasks (recurring, routine, mundane)
    ___ Accuracy concerns (avoiding mistakes in calculations and reports)
    ___ Compliance requirements (following accounting rules and standards)
    ___ Technology challenges (learning new software and tools)
    ___ Professional growth (gaining certifications, advancing career)
    ___ Internal communication (coordinating with colleagues)
    ___ Client relationships (responding to client needs)
    ___ Work-life balance (managing overtime, work fatigue, setting boundaries)
    ___ Data security concerns (protecting sensitive financial information)
    ___ Quality control pressures (ensuring consistency across team outputs)
    ___ Resource limitations (managing with budget/tool constraints)
    ___ Other (please specify): _____

4. What realized/potential benefits do you experience/anticipate from using Generative AI tools in your work to reduce the following concerns? (Please choose up to 3 concerns)
    a. ___ Faster completion of work and deadlines
    b. ___ Automation of routine tasks
    c. ___ Improved accuracy
    d. ___ Better compliance management

e. ___ Easier technology adoption
f. ___ Career advancement
g. ___ Enhanced team communication
h. ___ Better client service
i. ___ Improved work-life balance
j. ___ Stronger data security
k. ___ Consistent quality
l. ___ Optimized resource utilization
m. ___ Other (please specify): _____

5. What realized/potential negative impacts/concerns do you have about incorporating Generative AI tools into your workflow? (Please choose up to 3 concerns)
    a. ___ AI errors (mistakes in AI-generated outputs)
    b. ___ Review time (checking AI work for accuracy)
    c. ___ Data security (sensitive information leakage and system failures)
    d. ___ Technology dependence (reducing human judgment and practical skill development)
    e. ___ Job security (adapting to new roles)
    f. ___ Ethical issues (ensuring fair AI use)
    g. ___ Team interactions (changes in collaboration and knowledge sharing)
    h. ___ Learning needs (time to learn and onboard new tools)
    i. ___ Integration challenges (connecting AI tools with existing systems)
    j. ___ Other (please specify): _____

6. What are the unanticipated benefits and costs associated with Generative AI tools into your workflow? (Please specify): _____

For the following four questions, consider the functionalities of AI-assisted accounting software listed below:
Automated bank feeds
Matching and reconciliation
AI-powered financial statement preparation

1. What percentage reduction in task completion time do you expect with AI-assisted accounting software (e.g., Botkeeper, Vic.ai, and Truewind)? Example: A 20% reduction means a 5-hour task takes 4 hours; a 60% reduction means it takes 2 hours. (Select one answer.)
    a. None or Negative
    b. 0-20%
    c. 21-40%
    d. 41-60%
    e. 61-80%
    f. 81-100%

2. What percentage of routine tasks do you expect to be handled by AI-powered automation tools? (Select one answer.)
    a. None or Negative
    b. 0-20%
    c. 21-40%
    d. 41-60%
    e. 61-80%
    f. 81-100%

3. What percentage of transactions do you expect AI-assisted accounting software to classify without human review correctly? (Select one answer.)
    a. None or Negative
    b. 0-20%
    c. 21-40%
    d. 41-60%
    e. 61-80%
    f. 81-100%

4. What percentage of error reduction do you expect when using AI-assisted review and validation tools?
    a. None or Negative
    b. 0-20%
    c. 21-40%
    d. 41-60%
    e. 61-80%
    f. 81-100%

5. How do you expect the integration of AI-powered accounting tools to affect your job satisfaction concerning the following three aspects? (Select one per row.)

Productivity
Work-life Balance
Career

    a. Significant decrease
    b. Moderate decrease
    c. Slight decrease
    d. No change
    e. Slight increase
    f. Moderate increase
    g. Significant increase

To wrap up our study, please answer some final demographic questions about your work and organization.

6. What is the typical organizational size of your clients? (Select one answer.)
    a. Micro (< $5M annual revenue)
    b. Small ($5M - $50M)
    c. Medium ($50M-$500M)
    d. Large ($500M+)

7. Do you currently work in the United States? (Select one answer.)

8. If yes to the question above, in which state do you currently work?
    a. Alabama
    b. Alaska
    c. Arizona
    d. Arkansas
    e. California
    f. Colorado
    g. Connecticut
    h. Delaware
    i. Florida
    j. Georgia
    k. Hawaii
    l. Idaho
    m. Illinois
    n. Indiana
    o. Iowa
    p. Kansas
    q. Kentucky
    r. Louisiana
    s. Maine
    t. Maryland
    u. Massachusetts
    v. Michigan
    w. Minnesota
    x. Mississippi
    y. Missouri
    z. Montana
    aa. Nebraska
    bb. Nevada
    cc. New Hampshire
    dd. New Jersey
    ee. New Mexico
    ff. New York
    gg. North Carolina
    hh. North Dakota
    ii. Ohio
    jj. Oklahoma

kk. Oregon
ll. Pennsylvania
mm. Rhode Island
nn. South Carolina
oo. South Dakota
pp. Tennessee
qq. Texas
rr. Utah
ss. Vermont
tt. Virginia
uu. Washington
vv. West Virginia
ww. Wisconsin
xx. Wyoming

9. Which of the following best describes your employer? Select one answer
    a. Public accounting firm
    b. Private company
    c. Government/Public sector
    d. Non-profit organization
    e. Financial services company
    f. Consulting firm
    g. Self-employed/Independent Practice
    h. Other (please specify): _____