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Leveraging Artificial Intelligence in External Audit

A Strategic Proposal for an AI-Powered Automation Tool to Optimize Quality

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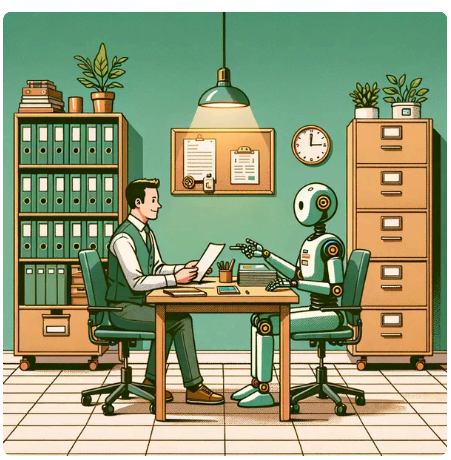

Abstract

The audit profession currently faces challenges in talent scarcity and increasing transaction volumes combined with the intensive nature of manual substantive procedures. This study aims to explore the challenges in manual vouching procedures, test the efficiency of the developed AI-powered vouching tool's performance, and explore auditors' perceptions of AI technology integrated into the audit process. The tool developed in this study was designed to automate the

vouching method. It incorporates a human-in-the-loop concept in the design logic to maintain professional oversight.

The researchers adopted a mixed-method approach that consists of semi-structured interviews to capture lived experiences of auditors and a comparative time-and-motion study to quantify efficiency gains in utilizing the AI-powered vouching tool. A post-manual vouching feedback survey was obtained from the participants who performed the manual vouching to gather insights on user experience.

The results revealed a 92% improvement [1]in processing time, reducing the average manual vouching time from 264.25 minutes (manual) to just 22 minutes (AI-assisted) across datasets. Furthermore, manual vouching resulted in a 50% exception detection rate and 75 data input errors across the 7 simulation cases embedded within the two datasets. Meanwhile, the AI tool achieved 100% exception detection rate with zero data input errors under the test conditions (n=7). The qualitative insights gathered from post-manual vouching survey highlight the cognitive fatigue experienced by the auditors and how volume and complexity introduced nuances in the manual process and user experience. The AI-powered vouching tool bridged these gaps by demonstrating operational consistency across different runs.

This study demonstrates that the AI-powered tool can accelerate audit tasks and transform the vouching process from labor-intensive and judgment-heavy efforts into deterministic, standardized workflows. The research contributes a framework for a transaction-level AI adoption in external audit by emphasizing that the developed technology serves to augment, rather than replace, the auditor’s capabilities.

Introduction

The audit practice is experiencing a declining number of CPA talents available in the market. Statistics have shown that there has been a 35% decrease in the number of candidates for the CPA licensure examination from 2019 to 2023 (Sison, 2023). This is compounded by the number of retirees, more stringent accreditation standards, and the growth of audit outsourcing firms decreasing the pool of talents for local audit firms. The lack of availability of sufficient numbers of

CPAs to meet the needs of audit clients creates challenges for audit firms particularly during the busy season which typically runs from January to April for audit firms serving the calendar year-end clients in the Philippines, when the majority of statutory audits are finalized.

Amidst the talent crisis, the volume of financial data handled by external auditors continues to grow. A critical component of this workload is vouching. Vouching, a component of the audit process, is a method used to substantiate the legitimacy and appropriateness of transactions recorded in the accounting records. Challenges identified by auditors associated with manual vouching include its repetitive, voluminous and labor-intensive nature, susceptibility to human error and human factors such as fatigue.

This research, motivated by the foregoing challenges, proposes an artificial intelligence (AI)-powered automated audit solution that leverages optical character recognition (OCR), template-assisted field extraction for structured document parsing and rule-based automated matching. The extraction module utilizes large language models (LLMs) to perform contextual recognition of the key invoice and delivery receipt attributes. Once the key data are extracted, they are subsequently processed through matching rules and threshold-based validation checks to flag potential exceptions. This modular AI-enabled design enables contextual recognition of unstructured and inconsistent data formats from heterogeneous documents, matches them against accounting records and flags exceptions for review. The human-in-the-loop (HITL) concept ensures that the professional judgment of auditors remains central to the process. This ensures that the workflow being developed supports transparency and external reviews, making it audit-defensible. The system operationalizes ISA 500's requirements by enhancing the reliability of evidence through rule-based matching and minimized manual encoding errors and strengthening traceability through exception logs and manual review logs. This paper addresses the following research questions:

- **RQ1:** What are the challenges and pain points encountered by auditors in performing manual vouching procedures?
- **RQ2:** To what extent can the AI-powered vouching tool improve audit productivity as compared to traditional manual vouching?

- **RQ3:** How do audit practitioners perceive AI technology being integrated into the audit process?

The empirical observations obtained from RQ1 shaped the design features and functionalities of the AI-powered vouching tool. RQ2 substantiates the role of the developed AI tool, demonstrating a 92% processing time improvement and eliminating data input errors. Finally, the integration of AI technologies in the audit workflow is contextualized through RQ3 where it is perceived as an effective tool in handling repetitive processes with greater accuracy. The study, thus, proposes a scalable, future-proof solution that can be deployed across firms and augment their operational efficiency.

This study makes a contribution to the literature on AI adoption in auditing by developing a transaction-level AI-powered vouching tool founded on practitioners' insights, exploring the challenges in vouching and analyzing auditors' perception of AI integration into the workflow. The developed AI-powered vouching tool demonstrates how AI can be operationalized within the boundaries of auditing standards such as ISA 500 (Audit Evidence) and ISA 330 (Audit Responses to Assessed Risks).

Literature review

The Role of Vouching in the External Audit

External auditing is a process of providing an independent service to a company to opine on the fairness of a company's financial statements. The objective of auditors is to obtain a reasonable assurance that the financial statements are free from material misstatement. This is done by performing a systematic examination of an organization's financial statements.

Vouching, a fundamental part of substantively testing the financial statement areas, supports occurrence/existence, completeness, accuracy and cut-off audit assertions. It plays a vital role in ensuring that the transactions recorded in the accounting system are well-supported by evidence such as invoices, delivery receipts and contracts. It involves tracing the information from the accounting records to the supporting documents. While it carries conceptual simplicity, it is a laborious, repetitive, and time-consuming process which involves detailed examination of the supporting documents. Multiple chains of documents such as purchase orders, sales invoices and delivery receipts make the process more complex as there is a need to cross-refer the information across different documents and trace it back to the accounting records. Furthermore, large samples require auditors to review large volumes of documents. Reliance on manual inspection introduces variability on the timeliness and quality of the output. The repetitive, voluminous characteristics of vouching make it an ideal candidate for automation which can streamline evidence gathering and matching of information in a precise manner.

Technological innovations and the rise of audit automation

The audit practice is continuously evolving driven by demands for increased productivity and accuracy. Audit firms are increasingly exploring and adopting automation tools to optimize audit workflows. Some of the most common foundational technologies being used are optical character recognition (OCR), which revolutionized digitized document handling, and robotic process automation (RPA), which enabled automating repetitive tasks, and laid the groundwork for advanced solutions.

The combination of OCR and RPA technologies can address inefficiencies in processing certain tasks. However, their capabilities are limited to data that have consistent formats and rule-based instructions (Cohen et al., 2019). However, these technologies lack the ability to process unstructured data from varied sources, a crucial element in the external audit as firms deal with clients in different industries. Furthermore, these technologies do not have the ability to recognize patterns, establish relationships, or exercise the adaptive reasoning necessary in vouching. AI addresses these limitations of traditional OCR and RPA technologies as it applies cognitive capabilities into audit workflows, enabling systems to perform tasks that traditionally would require human judgment (Riana et al., 2024).

Artificial intelligence (AI) is generally described as a set of technologies capable of performing cognitive tasks such as learning, solving problems, perception and understanding that traditionally required human intelligence (Davenport, 2018). In the context of process-level digital transformation such as vouching, the potential of AI combined with other technologies can fundamentally change the audit workflow. As AI can handle both structured and unstructured data (Bichel et al., 2023), and it can process large-scale document importing, extraction of key data, and matching of transactions, it has the ability to significantly improve coverage of verification while reducing errors.

Barriers and potential solutions for AI-aided audit support systems

AI's potential solutions are widely recognized in terms of improving efficiency, quality and scalability. However, for small and medium-sized auditing firms, AI applications remain constrained (Han et al., 2023; Kokina et al., 2025). Understanding the barriers to adoption is critical to ensure that the design and implementation strategies of the AI technology that will be developed intended for this study are aligned with the pain points of the users and the integrity of the audit process. The researchers' review of existing literature revealed key themes as discussed below.

One of the barriers is the high implementation costs of new technologies which involve upfront costs in infrastructure, software integration and recurring cost of system maintenance. The high investment cost remains a huge challenge particularly to smaller firms with limited resources (Han et al., 2023).

The integration of new technologies such as machine learning and data analytics requires technical competencies which are often absent in traditional audit training (Fedyk et al., 2022 and Kokina et al., 2025). Audit training is mainly focused on audit methodologies and accounting standards. The conventional framework of training auditors highlights the importance of collaboration between the IT and audit teams, targeted upskilling and continuous education in order to bridge this gap.

Consistency of data formats was cited by Kokina and Davenport (2017) as one of the main barriers preventing scalable implementation of AI technology as auditors deal with different clients with different data structure and document format. Lack of consistent formats and different types of unstructured data further introduces complexity in developing a tool that can handle supporting evidence and reports in varied formats.

Studies of Kokina et al. (2025) discussed that the main challenges in developing an AI tool are related to transparency and explainability, AI bias, data privacy, robustness and reliability, fear of auditor overreliance and the need for AI guidance. The “black box” nature of many algorithms affects transparency and explainability of the processing and the output it produces. As a result, it impairs auditors’ confidence and complicates their ability to justify conclusions, a crucial concern to auditor accountability (Kokina et al., 2025).

Empirical Evidence and Research Gaps

Despite the growth in empirical studies in AI applications particularly in external audit, most existing research remains conceptual and exploratory. Furthermore, the researchers found that most existing studies focus on AI’s role in the audit and its capabilities. Studies targeting transaction-level audit procedures such as vouching are limited and confined to qualitative methods. Studies of Onyenahazi (2024) and Nicolaidou (2024) explored AI’s potential in document matching; however, they lacked performance testing. Furthermore, the studies of Kokina et al. (2025) and Han et al. (2023) are supported by qualitative interviews as the methodology. Limited research tackling transaction-level AI application leaves gaps in quantitative evaluation of AI’s performance in terms of precision and reliability in the external audit landscape.

Thus, this study aims to address the gaps of existing empirical research by designing and testing an end-to-end AI-powered vouching tool.

Research methodology

Qualitative exploratory phase

A qualitative interview approach was utilized to equip the researchers with practitioners’ insights grounded in real-world context.

The researchers conducted semi-structured interviews with eight auditors from different audit firms. The researchers used the concept of thematic saturation to determine sample size (Aschauer & Quick, 2018) and they were selected via purposive sampling based on their experience in vouching and knowledge of technologies used in auditing. The interview questions covered three key areas: (1) professional background, (2) current vouching processes and challenges, and (3) perceptions of AI use in audit (Appendix 1). Follow-up questions were crafted to allow interviewees to express and develop their insights while ensuring that the main research themes were captured. The interviews took place between

September 2025 and November 2025 via one of the videoconferencing software programs. The researchers recorded the interviews verbatim with participants' consent and edited the transcripts thoroughly for accuracy. Table 1 includes a detailed list of participants in chronological order of our interviews.

Table 1: Participant demographic data

Participant Number	Position Title	Interview Number	Years of Experience	Company
P-1	Assurance Partner	I-1	29 years	Company A
P-2	Assurance Partner and Managing Partner	I-2	15 years	Company B
M1	Assurance Manager	I-3	6 years	Company C
S1	Senior Associate	I-4	4 years	Company D
S2	Senior Associate	I-5	3 years	Company D
M2	Assurance Manager	I-6	13 years	Company D
M3	Assurance Manager	I-7	6 years	Company D
M4	Assurance Manager	I-8	11 years	Company E

Both participant and firm names were coded for anonymity.

Following the six-phase framework (Braun and Clarke, 2006), the researchers conducted content analysis and developed themes supported by the descriptive coding techniques (Miles et al., 2014). Data obtained from the interviews were first condensed into analyzable segments, then descriptive codes were assigned based on the content and meaning (Miles et al., 2014; Creswell & Creswell, 2018; Doyle et al., 2020; Kokina et al., 2025).

Time-and-motion study

A time-and-motion study was employed in evaluating the AI-powered vouching tool's performance as compared with traditional manual vouching on the following dates: October 25, 2025, October 28, 2025, October 31, 2025 and November 1, 2025. Key performance indicators used were total time, average time, standard deviation, coefficient of variance, exception detection rate and data input errors to draw measurable outcomes from both the automated and manual vouching methods.

The researchers engaged different audit practitioners to perform the traditional manual vouching and the automated vouching to avoid carryover effects which may skew the results. Using purposive sampling, a total of four seasoned audit associates were recruited for the manual vouching method as they are directly responsible for executing vouching tasks. For the automated vouching, a professional was trained to run the AI-powered vouching tool to ensure that there's minimal user error and to reduce or eliminate any learning curve in the results.

The study involved two datasets, each comprising 50 simulated revenue transactions to reflect common audit scenarios. Business documents were solicited from independent entrepreneurs with identifying information anonymized for the purpose of the study. Document variations were introduced to reflect common audit scenarios. Dataset 1 comprised transactions supported by multi-page invoices and delivery receipts, while dataset 2 consisted of transactions supported by single-page invoices only. Both datasets consisted of simulated exceptions (Appendix 3) to assess exception detection performance.

After the participants completed the manual vouching task, a post-activity feedback form was gathered (Appendix 2) to gather qualitative feedback on user experience, perceived efficiency and difficulty and other insights to enrich the interpretation of the vouching results and provided insights in real-world audit practice.

Minimum viable product development

This study involves the development of an AI-powered vouching minimum viable product (MVP) to operationalize the empirical insights gathered from the study. It is designed as a Software-as-a-Service (SaaS) application accessible through a secured web-based platform. It includes functionalities of uploading transactions listing, ingestion of supporting documents, matching of information and exception reporting. The MVP incorporates human-in-the-loop design to confirm the system outputs. This design preserves professional judgment and oversight, and mitigates the risks associated with automation (Kokina et al., 2025). The integration of human-in-the-loop supports an explainable AI output, subject to professional skepticism (Zemankova, 2019).

The researchers collaborated with a software engineer to design and implement the MVP using real, business data solicited from independent entrepreneurs to simulate realistic audit conditions. The AI-powered vouching tool development phase had two main objectives: (1) to design an AI-powered audit tool with human-in-the-loop that can perform an end-to-end vouching and (2) to quantify potential improvements in efficiency and accuracy of the tool as compared with the traditional manual vouching by simulating real-world audit conditions.

Results and analysis

Thematic findings and analysis

A total of 110 coded statements were observed from the thematic analysis which yielded 88 unique codes. These were subsequently analyzed and synthesized which resulted in five overarching themes.

Challenges of Traditional Manual Vouching

The dominant insight gained from the interview revealed that vouching is considered by auditors as a laborious process. Most interviewees described it as time-consuming, voluminous, tedious, detail-oriented and inefficient. These findings are consistent with prior literature identifying conventional methods as time-consuming when conducting necessary audit procedures especially with larger datasets or samples (Hossain, 2025).

Inefficiencies were found to be compounded by the preparedness of the client, improper indexing, document quality issues, document format inconsistency and the number of exceptions flagged requiring further investigation. These pain points serve as the empirical basis for exploring technological interventions in vouching.

Human Resource and Structural Constraints

Resource constraints continue to pose challenges for auditing firms and among audit practitioners. Interview participants perceived that firms affiliated with large international audit networks (commonly known as “The Big Four”) attract a larger share of the talent pool, making it difficult for smaller firms to acquire people. For P2, the crisis in talent pipeline fueled a necessity-driven innovation for her auditing firm (Badghish and Soomro, 2024). P2’s reflection stated that, "We employed technology because we lack people". In order to combat the firm’s limited human resources, technology was employed not just for efficiency but to support manpower capabilities.

The shift to digital solutions is not without challenges as auditors face persistent learning curves and adoption is sometimes met with resistance to change. Seethamraju and Hecimovic (2022) have identified that talent adaptation and mismatched capabilities are core hurdles to digital development and adoption. It can be argued that while the current technology offers a solution, technology adoption’s success is still contingent on properly managing skills gap and technology integration. The technological learning curve reported by participants supports the study of Aljaidi et al. (2023) which highlights that the move towards data-driven auditing requires upskilling. Incorporation of technology necessitates the development of new abilities; auditors must become proficient in utilizing these tools to maximize the benefits and have an understanding of the ethical limitations associated with the use of technologies (Abdullah & Almaqtari, 2024). Technology adoption, in turn, inherently creates skills mismatch and a steeper learning curve, an additional layer of adaptation pressure on the current workforce.

Varying Level of Digitalization

Interviewees exhibited varying levels of digital maturity. P1, a partner in a firm with less than 20 employees, remains reliant on conventional audit processes stating that there is “no technology being used in the audit, just Excel”. Meanwhile, Big Four auditing firms have taken the lead towards developing technologies (Samiolo et al., 2023). P1 further explained that “the concern is the cost as technology has a cost, and it is usually high, so it may not be as efficient to implement to smaller firms as compared to big firms”. P2 emphasized rising subscription fees for their technology costs and the need to upgrade their hardware to handle the tool. The concerns of participants about high technology cost are universally recognized, as technologies require significant upfront and recurring costs (Han et al., 2023) which can strain the budgets of audit firms.

Furthermore, the degree of digitization among clients influences the extent of digital adoption of audit firms (Braun and Davis, 2022). Although the pandemic accelerated digitization, mixed modes of document provision were still reported by some participants.

Perceived benefits of AI in audit

Respondents who have adopted technologies for matching documents in vouching reported efficiency gains, improved turnaround times, reduced manual effort and more accurate results. S1, having a direct experience in using automation tools, shared his positive feedback as it reduced the vouching time by an estimated 50%. Respondents concurred that the use of automation tools allowed them to focus on analyzing insights (Cahyadi, 2020) and higher-value tasks (Goto, 2023) such as areas with significant risks, estimates and judgment.

The efficiency benefits of AI are well-supported by academic literature (Abdullah & Almaqtari, 2024 and Badghish & Soomro, 2024). Fedyk et al. (2022) reported substantial gains in quality among the audit firms who have invested in AI technology, as AI investments have been found to be associated with significant declines in the incidence of restatements, including material restatements and restatements related to accruals and revenue recognition.

Human-in-the-loop concept

A consensus among the participants emerged around the presence of a human-in-the-loop model as they recognize the indispensable role of auditors’ judgment, citing that AI technologies still require human intervention. OCR misreads, automation output errors and overreliance on system outputs were some of the risks highlighted by the participants. These views reflect a balanced approach to adopting AI by understanding its benefits on performance optimization, provided that validation protocols remain intact (Agrawal et al., 2018).

Empirical studies (Kokina et al., 2025, CAQ, 2024 and Onyenahazi, 2024) have a consensus view on the human-in-the-loop paradigm, which is founded on the concept that ethical reasoning and professional skepticism cannot be entirely transcribed into AI algorithms. This paradigm incorporates human judgment, oversight and intervention in AI-integrated workflows. The HITL approach allows humans to fix incorrect inputs and integrate human review which then reinforces transparency, especially given the “black box” nature of some AI systems (Kokina et al., 2025). The participants’ emphasis on the supplementary role of AI highlighted that the auditors view AI as a tool that can allow them to augment their work. As a result, human judgment and decision-making remain integral to automated workflows (Abdullah & Almaqtari, 2024).

Comparative time-and-motion study results and analysis

This section presents the time-and-motion study results for the manual vouching and AI-assisted vouching across two datasets. The results were interpreted using descriptive statistics.

Table 2: Time-and-motion results for manual vouching

	Dataset 1			Dataset 2 (invoices only)	Total minutes for the two datasets	Average minutes for each dataset
	Invoices	Delivery documents	Total minutes			
			A	B	A+B	(A+B)/2
Manual vouching						
Associate 1	75.00	158.00	**233.00**	**84.00**	**317.00**	**158.50**
Associate 2	58.00	122.00	**180.00**	**28.00**	**208.00**	**104.00**
Associate 3	79.00	180.00	**259.00**	**40.00**	**299.00**	**149.50**
Associate 4	61.00	126.00	**187.00**	**46.00**	**233.00**	**116.50**
Average manual time	**68.25**	**146.50**	**214.75**	**49.50**	**264.25**	**132.13**
Standard deviation	**10.31**	**27.54**	**37.72**	**24.19**	**52.06**	**26.03**
Variance	**106.25**	**758.33**	**1,422.92**	**585.00**	**2,710.25**	**677.56**
Coefficient of variance	**0.15**	**0.19**	**0.18**	**0.49**	**0.20**	**0.20**

The results in Table 2 show that manual vouching requires a significant processing time at an average of 264.25 to process both datasets. Dataset 1, which consists of multi-page documents, required more time to process as compared with dataset 2. Processing times across the two datasets performed by audit associates revealed a wide range of variability, suggesting individual differences in speed of vouching, document navigation and workflow approach.

The variability metrics in Table 2 provide context for processing time variability and consistency. The standard deviation and coefficient of variance (COV) showed moderate to high dispersion values, particularly for dataset 2 where COV registered at 0.49, which indicates that almost half of the processing time represented deviation from the mean.

For comparability, the processing time for both workflows included dataset-specific processing such as document matching, data extraction and reconciliation. For the AI-assisted workflow, the reported time includes file upload, automated processing and human review for those items flagged by the system.

In summary, the metrics shown in Table 2 emphasize key issues in performing manual vouching: (1) it incurs a significant amount of time, (2) the manual nature of the process produces inconsistency in processing times compounded by the nature of individual performance, and (3) it results in wide performance variation across auditors which makes time projection difficult to predict especially when met with tight timelines.

Table 3: Time-and-motion results for AI-assisted vouching

	Dataset 1			Dataset 2 (invoices only)	Total minutes for the two datasets	Average minutes for each dataset
	Invoices	Delivery documents	Total minutes			
			A	B	A+B	(A+B)/2
Automated vouching						
First run	9.00	9.00	**18.00**	**6.00**	**24.00**	**12.00**
Second run	6.00	9.00	**15.00**	**5.00**	**20.00**	**10.00**
Third run	6.00	9.00	**15.00**	**6.00**	**21.00**	**10.50**
Average processing time	**7.00**	**9.00**	**16.00**	**6.00**	**22.00**	**11.00**
Standard deviation	**1.73**	**0.00**	**1.73**	**0.58**	**2.08**	**1.04**
Variance	**3.00**	**0.00**	**3.00**	**0.33**	**4.33**	**1.08**
Coefficient of variance	**0.25**	**0.00**	**0.11**	**0.10**	**0.10**	**0.10**

Table 3 shows the results of the time-and-motion study for the automated vouching using the MVP developed by the researchers. Compared with the manual vouching, the AI-powered vouching tool processed invoices and delivery documents in dataset 1 and dataset 2 in an average of 16 minutes and 6 minutes, respectively. Across the three runs, the range of processing time across different components of each dataset is minimal. The variability measures in Table 3 support this observation. Standard deviation values were considerably low ranging from 0.58 minutes to 1.73 minutes, while variance measures registered at a range between 0.33 and 3.00 minutes squared. The results of coefficient of variance reinforce the high degree of performance stability.

The results of the measures of variability, which yielded minimal values, indicate the consistency of the AI-powered vouching tool's performance across repeated runs and highlight the deterministic nature of the AI-powered solution.

Table 4: Comparison between manual and AI-assisted vouching average processing times

	Dataset 1			Dataset 2 (invoices only)	Total minutes for the two datasets	Average minutes for each dataset
	Invoices	Delivery documents	Total minutes			
			A	B	A+B	(A+B)/2
Manual vouching (Table 2)	68.25	146.50	214.75	49.50	264.25	132.13
AI-assisted vouching (Table 3)	7.00	9.00	16.00	6.00	22.00	11.00
Improvement	61.25	137.50	198.75	43.50	242.25	121.13
Improvement (in %) [2]	90%	94%	93%	88%	92%	92%

Table 4 highlights the overall processing time improvement of 92% across all components by comparing the processing times between manual and AI-assisted vouching.

Overall, the comparative results provide strong evidence that the AI-powered vouching tool can process the tasks with a high level of speed and operational consistency. This supports the potential of the developed tool to improve process efficiency by reducing processing hours in a consistent manner.

Accuracy and Consistency of Manual versus AI-Assisted Vouching

In addition to efficiency and variability, the researchers have also evaluated the accuracy and consistency of detecting simulated errors across manual vouching and AI-assisted vouching and analyzed the naturally occurring data input errors, if any. The researchers analyzed two types of exceptions, namely, (a) simulated exceptions, or irregularities embedded by the researchers representing common audit deviations (Appendix 3), and (b) data input errors, which are errors carried out during the vouching process which may encompass encoding and document matching.

Table 5: Exception detection performance for manual and AI-assisted vouching

Dataset	Exception category	Nature of exception	No. of cases	% of manual detection	% of automated detection
Dataset 1	Simulated	Erroneous amounts, missing delivery receipt and incorrect date	4	50%	100%
Dataset 2	Simulated	Erroneous amounts and missing invoice	3	100%	100%

Table 5 shows the exception detection performance on simulated exceptions across both manual vouching and AI-assisted vouching. For results evaluation, an exception was considered “detected” if the workflow correctly flagged the transaction. Detection was assessed on a binary basis (detected vs. not detected), therefore, partial identification that did not correspond to the predefined criteria was not counted as a successful detection.

Associates were able to detect all simulated exceptions in dataset 2 as compared to 50% detection rate in dataset 1 which has a higher volume and entails more complexity. Meanwhile, the AI-powered vouching tool detected all simulated exceptions across all datasets. This highlights the ability of the developed tool to accurately perform the vouching process and its resistance to document variability that challenged the audit associates.

Generally, it was observed that simulated exceptions, such as amount or date deviations, were more consistently detected by the audit associates. This suggests that structured and numerical anomalies are easier to identify manually. Dataset 1, which has two sets of document types and has a higher page volume, negatively affected the performance of the audit associates. Dataset 1 demanded more cognitive effort as it requires (1) cross-referencing between invoices and delivery receipts, making the navigation more challenging, and (2) interpreting non-standard data formats. These findings reflect conditions encountered in real audit engagements where heterogeneity of document types, different data-formats and different volume levels obscures the process of exception identification.

A more revealing aspect of analysis came to light upon checking the accuracy and appropriateness of the working papers prepared by the audit associates. The researchers found that data input errors, which are naturally occurring errors, were committed by the participants during their manual vouching. These provide deeper insight into the challenges of conventional vouching workflows. The researchers synthesized and consolidated the errors into categories according to their similarities as summarized in Table 9.

Table 6: Combined Summary of Manual Data Input Errors by Category

Data input error category	Dataset 1	Dataset 2	Total
Unvouched Documents	2	1	**3**
Referencing Error	1	-	**1**
Incorrect Date or Date Format Errors	6	57	**63**
Wrong Customer or Vendor Name Inputs	4	4	**8**
Total	**13**	**62**	**75**

The automated document ingestion, parsing and matching eliminated common sources of human errors such as date formats, skipped documents and customer name inputs. The results highlight the tool's ability to reduce, if not eliminate, different consequential types of human error and inconsistencies such as transcription errors, skipped documents or misaligned references. While the results show efficiency and accuracy improvements, the limited number of simulated exception cases entails careful interpretation and further validation using larger datasets.

Overall, the accuracy findings complement the efficiency performance of positioning the AI-powered vouching not only acts as a productivity tool, but it also improves the reliability of output. This, in turn, helps to mitigate errors in performing substantive audit procedures. These findings are aligned with empirical research showing that the use of AI-assisted technologies leads to better quality as a result of fewer human errors (Kokina & Davenport, 2017).

Post-manual vouching feedback analysis

The researchers conducted a feedback session with the four associates who participated in the time-and-motion study through a structured questionnaire (Appendix 2) to evaluate user experience in vouching, perceived efficiency and difficulty, insights on potential automation and any other feedback they might have on the experience.

The participants highlighted the challenging nature of manual vouching. By drawing directly from their vouching experience across two datasets, the repetitive nature of the task led to reduced focus and slower processing. Furthermore, the volume and complexity were cited as participants experienced difficulties in navigating the documents and cross-referencing the required information across multiple supporting files back to the transactions listing. These factors, along with the voluminous nature of the transactions, contributed to cognitive and physical fatigue from sustained effort of validating the transactions listing by matching it with the supporting evidence.

Another theme that was observed is the perceived benefits of automation. The use of AI technology was viewed by participants as a valuable supplement to the audit practice. They recognize the potential of automated tools to handle repetitive processes with enhanced accuracy. This is aligned with the concept of augmented intelligence in auditing (Kokina & Davenport, 2017).

The last theme that emerged when asked about the insights on potential automation is the presence of human oversight as participants consistently cited the limitation of automation in exception handling. In the audit practice, resolving exceptions noted requires corroboration which involves inquiry with the client, review of other forms of evidence such as minutes of meetings and contracts, and validation with another source document to support or refute the initial finding. Resolving the exceptions to be able to come up with a conclusion is based highly on human reasoning and judgment.

The reflections gathered from the associates post-vouching contextualize the findings from the time-and-motion study and enrich the interpretive validity of the quantitative results presented in Section 5.2.

Discussion and Conclusions

Discussion of findings

Integrated synthesis of findings across different methodologies employed in this study revealed that vouching is a structural bottleneck in audit execution. Results of the time-and-motion study proved the labor-intensive nature of this audit process as the participants rendered a significant amount of time to complete the task. Furthermore, the processing time to manually vouch varies across different individuals as the conventional method involves a human cognition component with differing navigation strategies and document interpretation.

In terms of RQ1, findings from the interview and post-manual vouching feedback survey provided a layered perspective on the challenges and issues encountered in conventional vouching as detailed below.

- A consensus among the interviewees was observed in terms of the taxing nature of vouching. It was described as time-consuming, voluminous and laborious. Apart from the taxing nature of vouching, the recurring themes affecting the efficiency were document quality, date format inconsistency and exceptions handling. The information gathered from the semi-structured interview was consistent with the findings obtained from the post-manual vouching feedback. Apart from operational difficulties, insights gathered revealed cognitive drivers further straining human ability to focus and accurately perform the task.

- While operational inefficiencies and technology adoption dominate the discussion, a deeper analysis of human resource constraints resulting from a declining talent pool further contextualized its organizational and operational implications. As resource constraints affect the audit practice in general, some interviewees reported employing technology to combat this scarcity. Structural constraints observed in adopting technologies were resistance to change, mismatched skill set and learning curve.

- Rising technology or subscription costs and high upfront costs of the infrastructure were key barriers affecting technology adoption.

- The different levels of digital maturity of clients, as well as the modality of document provision, were found to be associated with the extent of digital adoption of audit firms. For clients who provide electronic records, automated tools and technologies can be utilized by auditors to improve efficiency.

The qualitative insights gained from the semi-structured interview served as the basis for the design logic, functional priorities and user interaction framework of the AI-powered vouching tool developed by the researchers in this study. The key themes gathered from the post-manual vouching feedback corroborated the findings in the semi-structured interview by giving a deeper insight into user experience. The empirical observations and insights gathered revealed operational challenges and cognitive limitations which validated the researchers' decision to automate vouching.

The time-and-motion study further reinforces the capabilities of the AI-powered vouching tool. In terms of RQ2, a 92% processing time improvement was observed in the time-and-motion study using the AI-powered vouching tool versus the manual method, combined with minimal variability of processing times across different runs. These findings validate the researchers' decision to automate the process that was empirically observed to consume a significant amount of time and effort during manual vouching. The speed of task execution, along with consistency and stability observed in different runs of automated vouching support existing empirical studies showing that AI alleviates inefficiencies in repetitive and rule-based tasks (Anantharaman et al., 2023, Abdullah & Almaqtari, 2024 and Badghish & Soomro, 2024). The quantitative results were corroborated with the post-manual vouching feedback analysis, where participants reported cognitive and physical strain associated with the volume, complexity and nature of the datasets. Participants reported that these challenges often lead to slower processing time and reduced focus resulting in higher susceptibility to human error.

Beyond efficiency, the findings from accuracy and consistency of error detection in manual vouching reveal vulnerability to simulated exceptions and data input errors. These findings are consistent with ICAEW (2023), which indicates that manual transcription errors are one of the most common sources of substantive audit misstatements. In terms of accuracy, the AI-powered vouching tool was evaluated and was found to detect all simulated anomalies with zero data input errors. This corroborates the empirical studies of Kokina & Davenport (2017), Fedyk et al. (2022), and Onyenahazi (2024), who argued that AI enhances audit quality by improving consistency and reducing judgment-dependence and other types of human errors. The data input error patterns guided the design features of the AI-powered vouching tool that relied on the AI’s ability to parse and interpret unstructured data from mixed types of documents and aims to reduce, if not eliminate, transcription errors.

The potential benefits and opportunities of integrating technology into the audit process are well-recognized by the interviewees and time-and-motion study participants. The following insights were drawn from our research for RQ3:

- The use of technology is perceived to positively impact audit workflows from the efficiency gains as it significantly lessens the time as it can handle repetitive processes and larger volumes of data with a high level of accuracy thereby reducing, if not eliminating, human error.

- Automation was viewed as a means to redirect efforts of audit practitioners to higher-value, higher-order tasks (Goto, 2023) such as analysis and interpretation.

- Despite the benefits, interview results and survey feedback highlight that AI-powered technologies serve as collaborative tools that can augment human capacity which aligns with the human-in-the-loop concept (Kokina et al., 2025, Agrawal et al., 2018 and CAQ, 2024).

Empirical insights gathered favor professional judgment integrated into the workflow. The researchers integrated the human-in-the-loop concept in the AI-powered vouching tool to strengthen human-AI interaction. In order to address interview findings of OCR misreads, ethical concerns and risk of overreliance on automated outputs, the developed AI tool includes features such as validation logs and explainable outputs to reinforce user confidence. This approach ensures that the AI-powered tool development is aligned with the auditor's risk appetite and the profession's ethical foundations. As a result, the design framework is structured around four main components:

- OCR for conversion of physical or scanned documents into machine-readable text;
- Intelligent document parsing capable of identifying and structuring key data fields from different data formats and heterogeneous documents;
- Automated rules-based matching which compares extracted data with ledger entries; and
- Exception reporting which flags mismatches for human review.

Figure 1: Mapping empirical findings to AI-powered vouching tool features

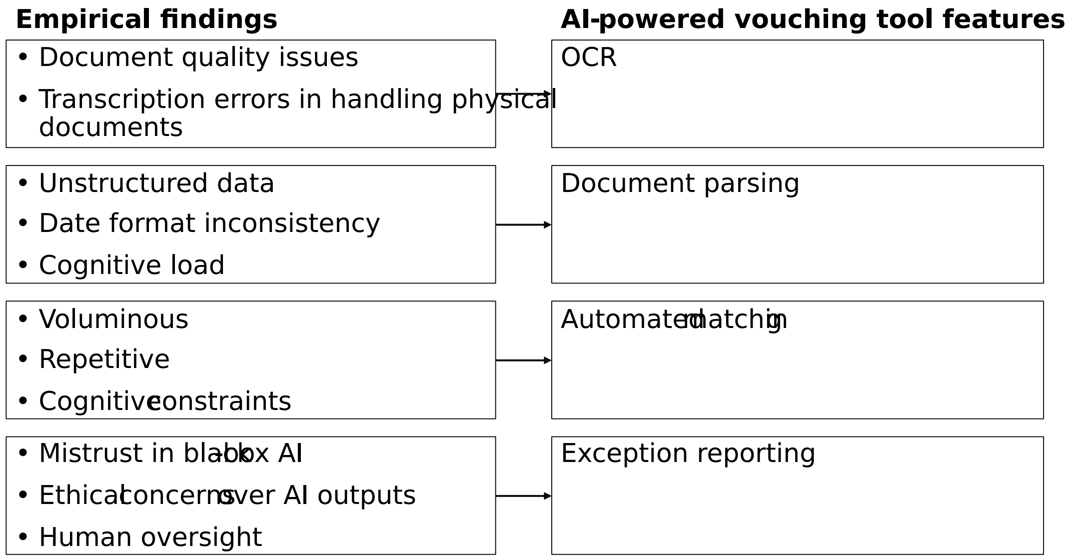

Figure 3 demonstrates how empirical insights were translated into functional features of the AI-powered vouching tool. This positions the AI-powered vouching tool as a response to real-world audit practice constraints rather than a purely technical solution to inefficiencies of manual vouching.

Managerial implications

To provide more context on the economic impact of utilizing the AI-powered vouching tool, two costing approaches were used by the researchers using realistic assumptions: (a) a charge-out rate model commonly used in engagement profitability analyses, and (b) a salary-based costing model reflecting actual internal labor costs.

Table 7: Illustrative Monthly Cost Savings from AI-Assisted Vouching

Assumption	Value	Explanation
Average working days per month	21 days	21 days for a given month were assumed at 8 hours per day
Productive hours per day	7.2 hours	8 hours per day x 90% productivity
Total productive hours per month	151.2 hours	Calculated as 21 × 8 × 0.90
Proportion of time spent on vouching	50%	Conservative estimate for transaction-heavy engagements
Estimated monthly vouching hours	75.6 hours	Calculated as 151.2 × 0.50
AI-enabled time reduction	92%	Time savings from the time-and-motion study
Hours saved per month (A)	70.0 hours	Calculated as 75.6 hours x 92%
Blended charge-out rate for associates (B)	Php800 per hour	Reflects the average charge-out of associates
Estimated monthly savings per auditor (A x B)	Php56,000.00	Calculated as 70.0 hours x Php800.00
Average hourly rate of associates (D)	Php178.57	Average hourly rate is based on the assumption of a monthly salary of Php30,000, divided by 21 average working days, divided by 8 hours per day
Estimated monthly cost savings per	Php12,500.00	Calculated as 70.0 hours x Php178.57

auditor (A x D)		

The assumptions above include an estimation of 21 working days for each month, at eight hours per day. A productivity factor of 90% was likewise assumed to incorporate non-billable activities and administrative duties. These assumptions will result in approximately 151.2 productive hours for each audit associate available per month.

Based on industry practice and researchers' professional experience, audit associate hours compose 50% of the total engagement hours. The audit associates' hours are allocated to areas that are transaction intensive such as sales/revenue, purchases, inventory and operating expenses. Applying this rate to the productive hours of associates yields 75.6 hours per month devoted to manual vouching activities. Applying the efficiency gain of 92% derived from the time-and-motion analysis conducted in this study results in approximately 70.0 hours saved per audit associate per month.

To translate the time savings of 70 hours per audit associate per month, a blended charge-out rate of Php800 per hour was utilized. This reflects the average billing rate for associate auditors for rendering engagement hours to each client assigned to them. It incorporates salary costs and benefits, overhead recovery and engagement profitability.

Using the foregoing assumptions, an estimated monthly savings of P56,000 per auditor was calculated, or approximately Php672,000 annually if the productivity level is sustained across a full year. The figures in Table 10 illustrate the economic benefits from AI adoption, particularly for firms with large portfolios of high-transaction clients.

To capture the actual savings to the firm, the researchers utilized a second approach that uses the auditor's average salary. Assuming an average monthly rate of Php30,000 for the audit associates, the hourly cost registers at Php178.57 per hour. Applying this rate to the estimated 70 hours saved per month yields an estimate of Php12,500 actual cost savings per month (or roughly Php150,000 annually).

The foregoing analysis emphasizes the economic benefits of adopting technologies such as AI which are widely emphasized in audit digitalization literature (Sutton et al., 2016; Seethamraju & Hecimovic, 2022). Apart from cost reduction, integrating AI technology allows for strategic reallocation of efforts toward higher-value procedures that require skepticism and human judgment such as analytical review, exception handling, risk assessment and client coordination. This supports the role of AI in enhancing audit quality documented in the literature on assurance digitalization (Kokina & Davenport, 2017; Fedyk et al., 2022; and Seethamraju & Hecimovic, 2022).

The time-and-motion study revealed that the AI-powered vouching tool can process voluminous transactions. In audit practice, transaction-intensive cycles are high-impact targets where the tool can be utilized.

The perceived opportunities of integrating AI into the audit process were well-recognized by the interviewees. This suggests openness of auditors in adopting new AI tools. Upskilling and capacity building are necessary to bridge the gaps towards a successful technology adoption. One of the recurring themes that arose in the semi-structured interview is the human-in-the-loop concept. Technology acquisitions should consider oversight structures embedded into its technological tools to ensure that automation enhances, rather than compromises, audit quality (CAQ, 2024).

Conclusions and future research

This study provides empirical evidence that an AI-powered vouching tool, designed with a human-in-the-loop architecture, can materially enhance audit efficiency while preserving professional judgment and oversight. The time-and-motion results demonstrate substantial reductions in manual processing time, and the costing analysis translates these efficiencies into economically meaningful savings at both the engagement and firm levels. Beyond operational gains, the embedded exception-reporting and review checkpoints reinforce compliance with ISA 500 and ISA 330 by ensuring that automation supports — rather than substitutes for — auditor judgment.

The findings contribute to the growing literature on audit digitalization by offering a process-level examination of AI implementation within a specific audit procedure. Whereas prior studies largely examine AI adoption at the conceptual or firm level (e.g., Kokina & Davenport, 2017; Seethamraju & Hecimovic, 2022), this study demonstrates how AI can be operationalized within a discrete audit task and empirically measures its efficiency implications. The human-in-the-loop structure further responds to regulatory and professional concerns regarding accountability and audit quality in automated environments (CAQ, 2024; Samiolo et al., 2023). In doing so, the study positions AI not as a replacement for auditors, but as an augmentation mechanism that reallocates effort toward higher-value tasks requiring skepticism, analytical reasoning, and client interaction.

From a practical perspective, the results suggest that transaction-intensive audit cycles represent high-impact entry points for AI integration. The positive perceptions expressed by practitioners indicate readiness for technological transformation, provided that appropriate training, governance mechanisms, and oversight structures are embedded within the system. Successful adoption therefore depends not only on technological capability, but also on organizational preparedness and upskilling initiatives.

Despite its contributions, this study has limitations that provide avenues for future research. First, the time-and-motion experiment reflects a single exposure per condition, capturing initial performance rather than stabilized proficiency levels. Future studies may incorporate repeated trials to examine learning curve effects and longer-term productivity outcomes. Second, the empirical setting is confined to one national context and a limited number of practitioners. Expanding the sample across firms, jurisdictions, and audit tiers would enhance generalizability. Third, the analysis focuses primarily on efficiency metrics; subsequent research may examine broader quality indicators, including error detection rates, audit documentation quality, and regulatory inspection outcomes.

As audit environments continue to evolve under Industry 4.0, understanding how AI tools can be responsibly integrated into assurance processes remains critical. This study offers preliminary but concrete evidence that thoughtfully designed AI systems anchored in human oversight can transform routine audit procedures into more efficient, strategically focused, and quality-enhancing practices. Continued interdisciplinary research will be essential in shaping governance frameworks that ensure AI adoption strengthens, rather than dilutes, the credibility of the audit profession.

Appendix 1

The interview questions are as follows:

Research question	Key interview questions
Introduction	· Can you describe your role and experience? · How long have you worked in the external audit profession, and in what capacity/role?
Vouching process and challenges	· How would you describe the vouching process? · What types of documents are involved in this process? Are they usually electronic or hard copies? · What challenges do you encounter when doing manual vouching?
Openness to AI in audit	· Have you used any form of audit automation or AI-assisted tools before? If yes, which ones? · What is your initial impression of using AI tools in audit? Do you see it as a support tool or replacement risk? · What concerns (if any) do you have about AI performing validation tasks?

Appendix 2

The post-manual vouching feedback questions are as follows:

Sections	Interview questions – post-manual vouching
User experience	· Describe your overall experience performing the manual vouching task. Which part of the process took the most time or effort?
Perceived efficiency and difficulty	· On a scale of 1 to 5, how difficult did you find this vouching exercise? (1 = very easy, 5 = very difficult) · What made the process easier or harder for you?
Reflections on potential automation	· Do you think automation could reduce errors or mismatches? Why or why not? · Are there any parts of the process you believe should remain manual (e.g., judgment calls, exceptions)?

Appendix 3

Simulated exceptions planted by the researchers in the datasets are as follows:

Dataset 1

- Sample 9 date was changed from May 22 to June 22
- Sample 13 amount was changed from Php145,845.16 to Php145,854.16
- Sample 39 amount was changed from Php91,235.36 to Php91,325.36
- One delivery receipt cannot be matched to any item in the dataset

Dataset 2

- Sample 23 amount was revised from Php1,737,158.50 to Php1,747,158.50
- Missing invoice for sample 33
- Sample 48 was revised from Php11,287,864.64 to Php11,278,864.64

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Footnotes

1. Where, percentage reduction in processing time = (Manual time – AI processing time)/Manual time x 100 ↑

2. Where improvement in processing time = (Manual time – AI processing time)/Manual time x 100 ↑

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