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The Effect of AI-Enabled Accounting Systems on Employee Productivity and Financial Process Performance: An Empirical Investigation

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Abstract: The research paper will focus on a quantitative research method, where the operational performance data and questionnaires will be conducted to accounting professionals and financial managers of organizations that utilize AI to different extents. The key performance indicators will be invoice processing time, reconciliation time, and rate of transaction errors, task turnaround time of financial reporting, and the rate of employee task completion. Comparative analysis will be performed where the data on accounting processes exist before and after the introduction of AI to determine performance. The correlation analysis, descriptive statistics, and multiple regressions will be used to analyze the correlation between the adoption of AI-enabled accounting systems, employee productivity, and financial processes performance and consider other organizational and technological factors. It is anticipated that the findings would add to the existing body of research on the transformative accounting technologies driven by AI and that it would offer practical insights to companies, individuals accountants, and policymakers aiming to streamline their financial processes with the help of AI-based technologies.

Keywords: Artificial Intelligence, AI-Enabled Accounting Systems, Employee Productivity, Financial Process Performance, Accounting Automation, Operational Efficiency, Financial Reporting, Digital Transformation.

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1. Introduction

1.1 Background of the Study

The quick development of the concept of artificial intelligence (AI) impacted the digitalization of business processes in many aspects and accounting and financial management in particular. Intelligent technologies are becoming more popular with organizations seeking to automate monotonous operations, get a better handle on the accuracy of financial data and speed up the processing of transactions and boost organizational efficiency. Traditionally known to involve much manual entry of data, verifying transactions, financial reconciliation, and periodic reporting, the accounting functions are heavily evolving with the incorporation of AI-enabled accounting systems. The path has provided opportunities to organizations to enhance performance of operations and redefined the functions and productivity of accounting professionals (Kokina & Davenport, 2017; Moll & Yigitbasioglu, 2019). The term artificial intelligence is used as a general concept of the ability of computational technologies to perform tasks related to human cognitive processes such as learning, pattern recognition, classification, prediction, and decision support. In accounting settings, intelligence systems based on AI have the potential to involve machine learning, natural language processing, intelligent document recognition,

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predictive analytics, and generative AI. These features can work alongside numerous accounting capabilities, such as automated invoice handling, assignment of transactions, bank reconciliation, the supply of financial statements, detection of anomalies, and regular maintenance.

1.2 AI-Enabled Accounting Systems and Employee Productivity

In the accounting departments, productivity of employees can be evaluated in terms of measurable metrics like number of invoices handled by an employee, transactions done by an employee in a given work hour, number of reconciliations done by an employee within a given deadline and number of accounting tasks accomplished by an employee within a given reporting period. Productivity is not hence confined to how employees believe they are efficient, but also checked using observable performance in their operations. The correlation between employee productivity and adoption of technology has attracted a lot of interest in information systems and organization studies. Goodhue and Thompson (1995) had suggested the Task-Technology Fit model where they asserted that information technology enhances the level of individual performing when it has the capability to match the demand of the task at hand.

1.3 AI-Enabled Accounting Systems and Financial Process Performance

Financial process performance is the effectiveness and efficiency of organizations in terms of accounting and financial management. It includes the speed, accuracy, reliability, consistency, resource efficiency of financial operations. Process performance is especially significant in the accounting departments since any delays or mistakes in the daily financial operations can interfere with the reporting timelines, managerial judgment, processing payments, financial controls, and general accuracy of organizational financial data. AI-based accounting systems can enhance the performance of financial processes via a number of mechanisms of operation. First, intelligent automation can lead to the decrease of the processing time, i.e. decrease of the repetitive data-entry operations, and increase the speed of the flow of financial information between applications that are interlinked. Second, AI-to-be-supported classification and verification could improve accuracy by showing which transactions need more attention and identifying inconsistencies.

1.4 Research Problem and Existing Literature Gap

Processing delays and errors in data-entry can be experienced when these activities are done manually. The invoice-processing systems based on AI can automatize the selected phases of documents recognition, information mining, authentication, and typology of transactions. Performance can thus be measured using measures like average processing time per invoice, the resistance of invoices processed manually as compared to those completed without manual intervention and the number of invoices completed by each employee and the frequency of error in processing invoices.

Chapter Two: Literature Review

2.1 Introduction

The growing adoption of intelligent systems in accounting tasks has provided chances to automate regular financial operations, enhance the precision with which financial transactions are processed, eliminate delays in operations, and also raise productivity of employees. To better streamline financial processes, organizations are increasingly using AI-based applications in tasks like invoice, account, and transaction classification, financial reporting and routine bookkeeping.

2.2 Conceptual Review of Artificial Intelligence in Accounting

2.2.1 Concept and Development of Artificial Intelligence in Accounting

In an accounting context, AI programs are becoming more popular to analyze both structured and unstructured financial data, automate transaction-processing functions, identify suspicious accounting entries, and assist in making professional decisions. The advent of AI is another step in the historical evolution of accounting information systems. The traditional accounting systems were originally aimed at computerizing the bookkeeping records and simplifying the preparation of financial statements. Enterprise resource planning systems then boosted the coordination of accounting data within organizations in the departments. The more recent advances in automation and AI also have expanded those capabilities by allowing intelligent processing of financial information and reducing the participation of employees in their chosen routine accounting tasks (Moll and Yigitbasioglu, 2019). Kokina and Davenport (2017) offered one of the first focuses on the AI in the accounting and auditing field and found the chances of smart systems redeveloping work practices.

2.2.2 Types of AI Technologies Used in Accounting

Machine learning enables machines to learn the characteristics of past financial data and build a model of classification or prediction. In accounting, these capabilities could be used to aid in categorizing transactions, anomaly detection, account coding and identifying unusual financial activity. Machine learning systems have the potential to enhance better classification in the instances that there are enough pertinent training data, but their reliability wonders on the quality of the data as well as the consistency of the underlying financial patterns. Natural language processing

(NLP) allows to transform how computers analyze and comprehend natural language. NLP can be used in accounting to process the description of invoices, financial documentation, transaction descriptions, contracts and other textual data. In combination with document recognition technologies, NLP can also facilitate the extraction of accounting information on unstructured documents. Optical character recognition (OCR) is a process that converts text in scanned books or images to a machine-readable format. Not all OCR systems are AI systems per se, but current intelligent document-processing software often uses OCR alongside machine learning and NLP to identify the structure of financial documents and devise all useful accounting information.

2.3 AI-Enabled Accounting Systems and Employee Productivity

2.3.1 Concept of Employee Productivity

Employee productivity can be defined as the efficiency by which employees will change the working time, effort, knowledge and organizational resources into the finished outputs. In the accounting departments, productivity can be measured by the number of accounting transactions carried out, the amount of financial activities undertaken and the time taken by employees to perform some routine duties. Customary measurements of productivity often focus on output in relation to work input. But, more needs to be done to the accounting profession to focus on the reliability and accuracy of work done. It may not guarantee superior productivity to process a larger number of transactions that may have lots of errors or have to be corrected. In this vein, the performance of employees working in an AI-enabled accounting context can be construed as the effective accomplishment of correct and trustworthy accounting processes within the working time conditions. They can be potential indicators such as invoices paid per employee-hour, transaction per working day, reconciliations made per employee, accounting activities that will be completed within a deadline, and the ratio of time of the employee that was spent on productive financial behavior(Adun et al., 2022)(Dalal, 2020) (Adun et al., 2023).

2.3.2 AI Automation and Employee Task Completion

AI-based accounting can enhance staff efficiency as less time and effort can be spent on repetitive processing operations. Cooper et al. (2019) conducted research on the use of RPA in accounting firms and interviewed accounting professionals to find out information about the application. Their study reported some enhancement in processing efficiency, such as significant decrease in time to complete selected automated activities. Interviewees stated processing-time improvements of about 70 percent-80 percent in certain applications, but these numbers were organizational experiences as opposed to a controlled experiment (Ogungbemi et al., 2022) (Mohammad & Mahjabeen, 2023).

2.3.3 Evidence of AI-Related Productivity Improvements in Accounting

Over 200,000 accounting transactions data were used in the field analysis. It was discovered that the implementation of generative AI was linked with a rise in counting efficiency, as well as a shift in employee spending. Increased use of AI was associated with the less time spent on data entry and more time spent on business communication and quality assurance. In particular, an increase in the generative AI utilisation by one standard-deviation amounted to a decrease in the fraction of working hours spent on routine data entry by about 2.6 percentage points, or about 1 hour in a 40-hour workweek. The results of this study indicate that the implementation of AI can enhance productivity in two ways (Hegde & Varughese, 2022) (Maizana et al., 2023) (Dalal, 2018).

2.4 AI-Enabled Accounting Systems and Financial Process Performance

2.4.1 Concept of Financial Process Performance

The pertinent dimensions are the processing speed, accuracy of transactions, on-time reporting, reliability of the workflow, and effective use of accounting resources. These dimensions can be impacted by AI-enabled systems as they can provide increased speed in the information extraction process, lessening repetitive processing needs, assisting in transaction validation procedures, and enhancing the accessibility of accounting data(Karmakar, 2021)(Tansu et al., 2022)(Dalal, 2018).

2.4.2 AI and Invoice Processing Efficiency

Invoice-processing systems powered by AI have the potential to combine document recognition, machine learning, and automated processes to decrease manual effort of these operations.The researchers evaluated the prototype using an independent sample of 25 invoices. Their results indicated that three invoices required manual intervention, representing an exception rate of 12%(Hegde & Varughese, 2022) (Dalal, 2018).

2.5 Empirical Evidence on AI Adoption and Accounting Performance

2.5.1 Earlier Research on Accounting Automation

Earlier empirical studies established an important foundation for understanding the organizational effects of automation in accounting.

Cooper et al. (2019) investigated the implementation of RPA within public accounting firms and documented reported improvements in processing efficiency, work organization, and employee responsibilities. Their findings indicated that

automation could reduce repetitive work and enable accounting professionals to devote greater attention to higher-value activities(Tiwari, 2022) (Bahadur et al., 2022) (Dalal, 2019).

2.5.2 AI Investment, Accounting Quality, and Operational Efficiency

Their results were that increased AI investment was linked to the increase in the audit quality and lowered audit fees. In particular, a one-standard-deviation rise in the recent AI investment was correlated with a 5.0-percent decrease in the probability of an audit restatement and a 0.9-percent decrease in audit fees.

2.5.3 AI Adoption and Internal Control Performance

Nevertheless, another potential implication revealed in the findings was that monitoring activities might diminish as organizations feel that the newly instituted automated systems are trustworthy by default. The implications of this finding to the experience of research into performance of an accounting process can be critical (Hegde, 2021) (Mohammad & Mahjabeen, 2023) (Dalal & Abdul, 2019).

Chapter Three: Research Methodology

3.1 Introduction

This chapter presents the research methodology proposed to investigate the relationship between AI-enabled accounting systems, employee productivity, and financial process performance. (Ashraf, 2025; Choi & Xie, 2026).

3.2 Research Design

The research design that will be implemented in the study will be quantitative research design that will involve the use of explanatory and comparative approaches. The explanatory approach will examine the correlation between implementation of AI-enabled accounting system and accounting performance, whereas the comparative approach will consider operational differences prior to and after AI implementation or of the organisations with different degrees of AI implementation(Mohammad & Mahjabeen, 2023) (Adun et al., 2 22) (Dalal, 2020).

3.3 Research Population and Sampling

Where possible, a stratified sampling method will be employed with the aim of providing representation of the various levels of AI implementation. The degree of AI usage in accounting activities will be used to classify the organizations into low, moderate, and high AI-adoption(Adedeji et al., 2022) (Dalal, 2020) (Hegde & Varughese, 2020).Since the operational comparisons address both organizational and employee level observations, the statistical precision will also focus on the number of organizations that will take part in the operation comparisons.

3.4 Data Collection Methods

The study will collect primary and secondary operational data.

Primary data will be obtained through structured questionnaires administered to accounting employees and financial managers. The questionnaires will capture information about AI implementation intensity, system utilization, employee training, task-technology fit, and organizational support(Dalal, 2020) (Hegde, 2019) (Mohammad et al., 2022).Secondary operational data will be obtained, where authorized, from accounting system records, transaction logs, financial reports, and workflow management systems.

The main operational indicators will include:

1. Average invoice processing time.
2. Account reconciliation completion time.
3. Transaction classification error rates.
4. Financial reporting turnaround time.
5. Employee task completion rates and transaction throughput.

3.5 Reliability and Validity

Cronbach alpha will be used to determine the reliability of the questionnaire constructs and a value of 0.70 or higher is normally deemed to be satisfactory in exploratory research (Nunnally and Bernstein, 1994).

3.6 Data Analysis Techniques

Operational performance will be compared before and after the implementation of AI using paired-sample t-tests, or the relevant nonparametric counterparts. To compare the organizations implementing AI at different levels, analysis of variance (ANOVA) can be applied. The results of multiple regression analysis will help investigate the dependency between the level of AI implementation on one hand and productivity of employees or financial processes on the other hand, conditional upon the organizational and technological features. The general regression model will be given as:

$$Y_i=\beta_0+\beta_1AI_i+\sum_{k=2}^{K}\beta_kX_{ki}+\varepsilon_i$$

Where:

- Y_i = employee productivity or financial process performance.
- AI_i = AI implementation intensity.
- X_{ki} = control variables, including organizational size, transaction volume, and process complexity.

- \(\beta_0\) = regression intercept.
- \(\beta_1\) = coefficient estimating the association between AI implementation and performance.
- \(\varepsilon_i\) = error term.

Chapter 4: Results and Interpretation of Figures

Operational performance will be compared before and after the implementation of AI using paired-sample t-tests, or the relevant nonparametric counterparts. To compare the organizations implementing AI at different levels, analysis of variance (ANOVA) can be applied. The results of multiple regression analysis will help investigate the dependency between the level of AI implementation on one hand and productivity of employees or financial processes on the other hand, conditional upon the organizational and technological features. The general regression model will be given as:

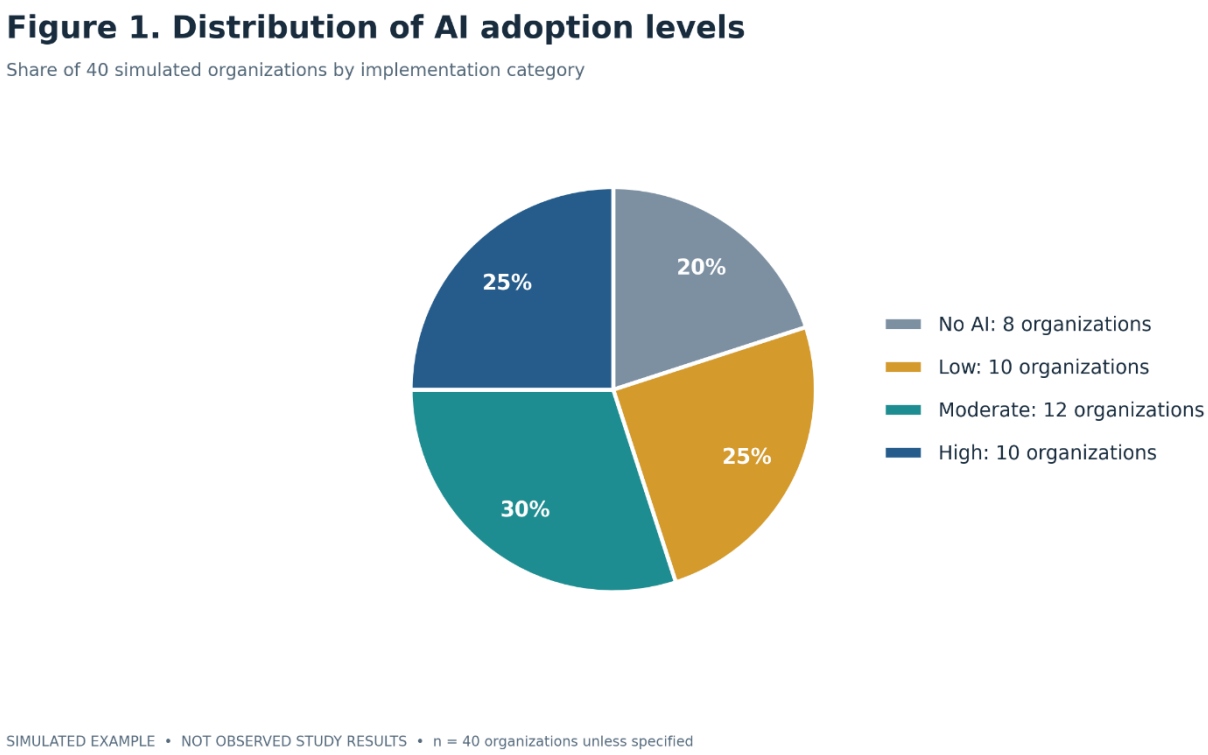


Figure 1. Distribution of Organizations by Level of AI-Enabled Accounting System Adoption

Figure 1 shows how 40 simulated organizations were distributed based on whether they adopted an AI-enabled accounting system or not. Results show that one out of every three institutions is moderate in terms of AI adoption, which is then complemented by 25 of high AI adoption types and 25 of low AI adoption types. The other 20% of the organizations that are not yet using AI-enabled accounting technologies represent the remaining 20% of the organisations. Such dispersion implies that within the illustrative sample, there are organizations at different levels of technological adoption. The share of the sample held by organizations moderately and highly AI adopted is 55% indicating a significant percentage of the hypothetical organizations have adopted AI in at least some processes within their accounting. Variations in the level of adoption will offer a platform on which the question of a more profound adoption of intelligent accounting technologies correlates with higher performance of employees and financial processes can be contemplated.

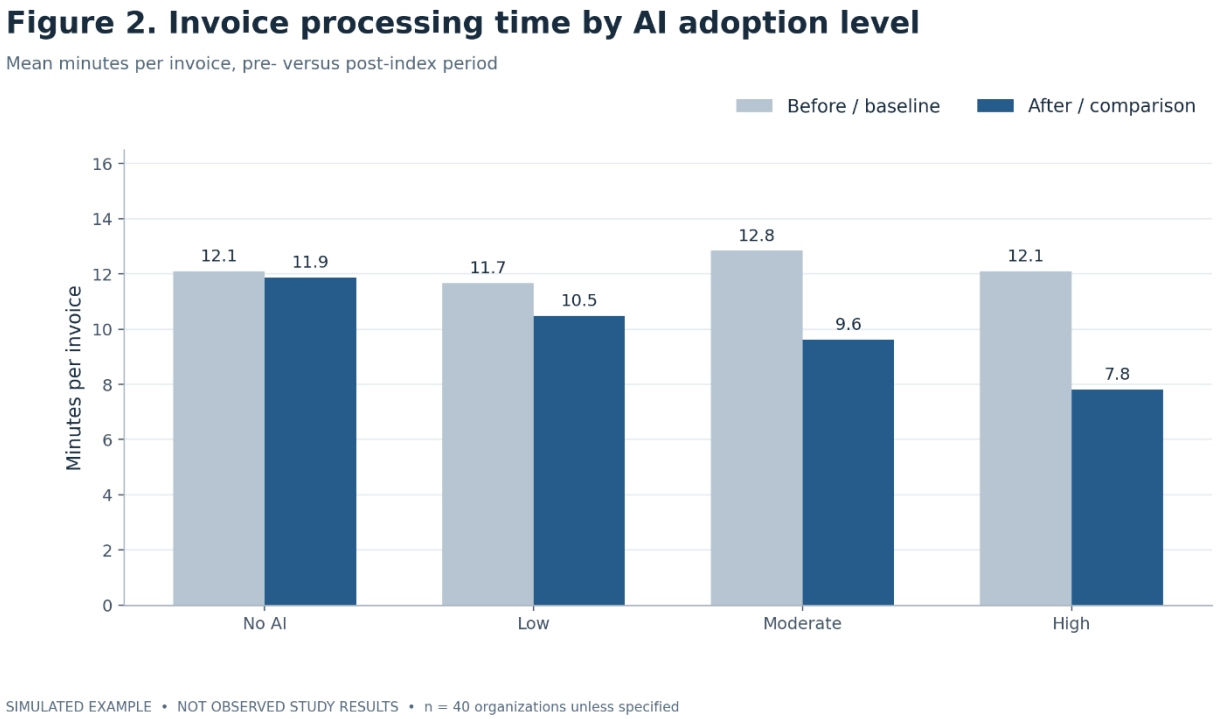


Figure 2. Comparison of Invoice Processing Time Before and After AI-Enabled Accounting System Implementation

Figure 2 contains a comparison of an average invoice processing time in organizations of various AI levels. The simulated outcomes reveal that the average time of processing invoices by the organization was reduced in high AI implemented organizations by almost 12.10-7.82 minutes per invoice. Organization that had moderate usage indicated the decrease of 12.84 minutes to 9.62 minutes and those that had low usage of AI indicated a decrease of 11.67 minutes to 10.48 minutes. Companies that did not utilize AI showed slight variance between the comparison period and baseline. Such exemplary results can be interpreted to mean that the more AI is implemented, the more beneficial may be the invoice processing. Such improvements may be based on intelligent document extraction, automated transaction classification, and decreased manual data entry. But to determine whether these differences are significant or not, statistical testing based on real records in an organization would be required.

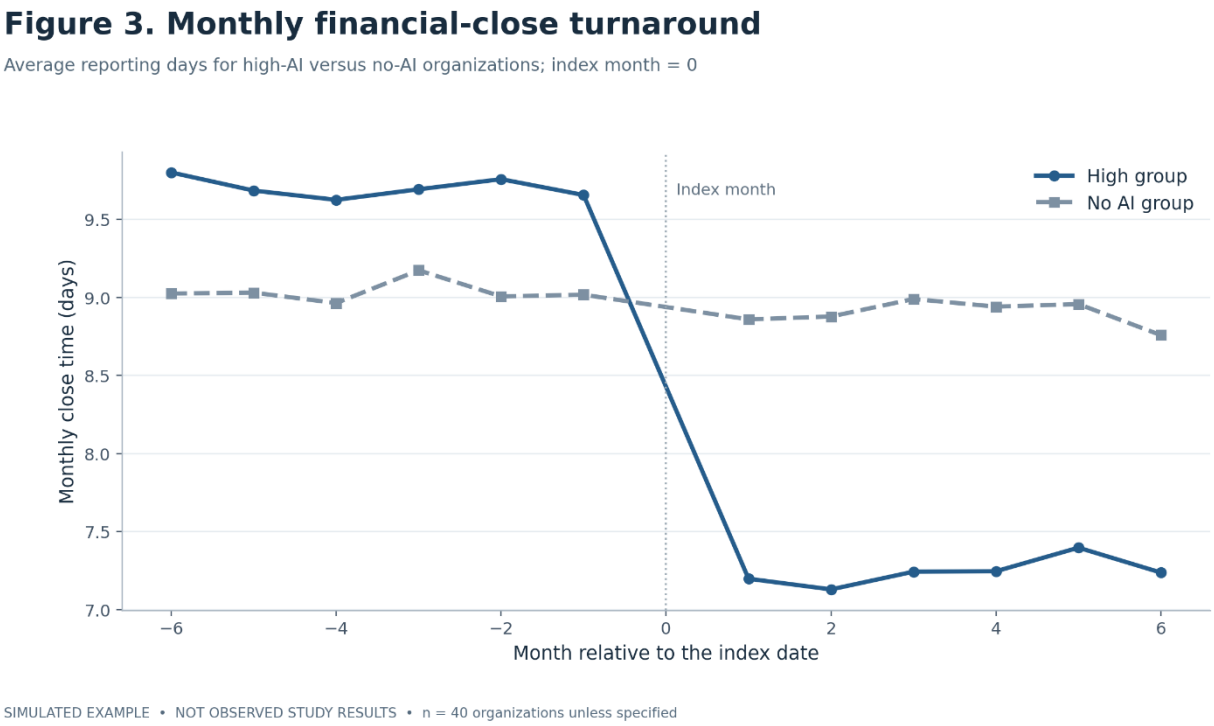


Figure 3. Trend in Financial Reporting Turnaround Time Before and After AI Implementation

Figure 3 demonstrates the turnaround time of monthly financial reporting of organizations that have high AI adoption, and those that do not implement AI. The graph shows 6 simulated pre-implementation months and 6 simulated post-implementation months of a date of hypothetical implementation. The findings from the research reveal that in the case of high AI implementation, an average monthly financial closing time was lowered by some 9.70 days to about 7.24 days. Contrastingly, the reporting period in organizations that do not use AI was comparatively constant, decreasing by 0.04-0.90 days.

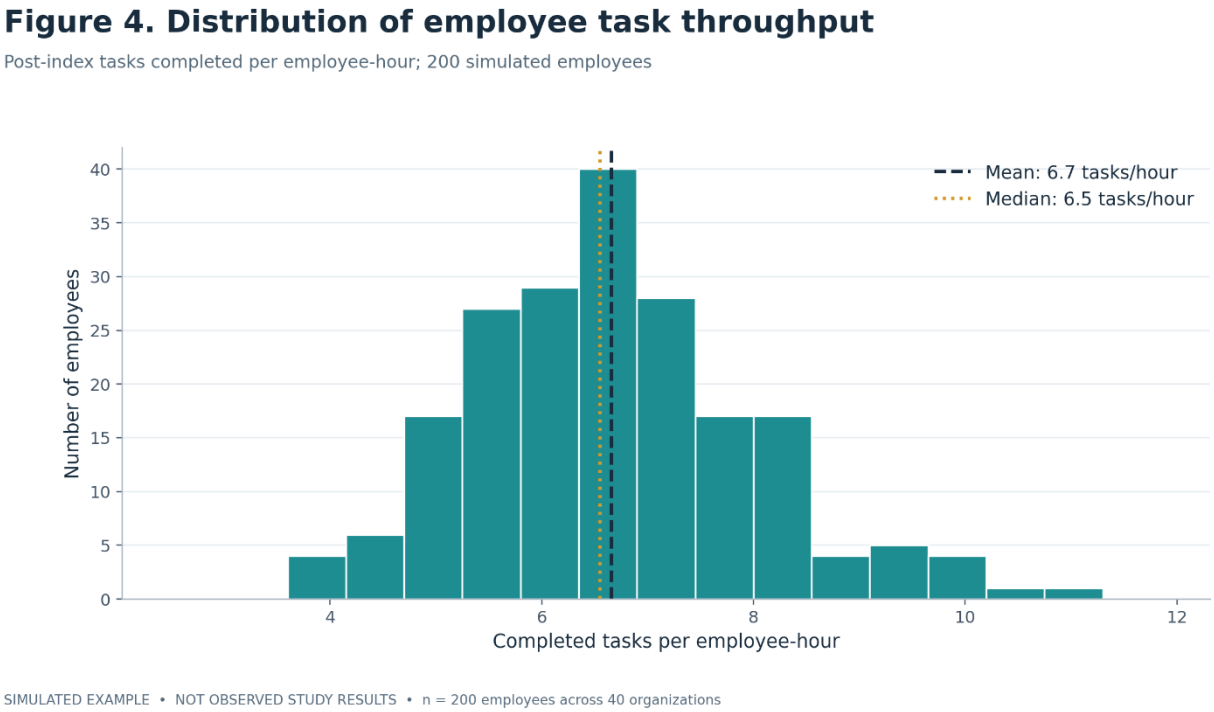


Figure 4. Distribution of Employee Task Completion Rates in AI-Enabled Accounting Environments

In Figure 4, the accounting task completion rate is given as the percentage of 200 (hypothetic) employees in 40 (organizations) got exposed to accounting job completion. Measurement of post-index period The productivity of employees will be in the number of accounting tasks completed per employee-hour. The simulated outcomes indicate that the average rate of productivity is about 6.66 tasks per hour with a median productivity rate of 6.55 tasks per hour. The histogram depicts variance in employee productivity with certain employees finishing off the few tasks and others showing a significant higher throughput. These differences can be manifested in the difference of AI application, the experience of employees, technological fit, and the complexity of tasks in accounting. The figure helps to focus on the importance of analyzing productivity distributions, instead of using organizational averages. Nonetheless, individual differences in task completion rates with AI should not be added to the list of factors that are predetermined by AI adoption without controlling variables of employees and organization.

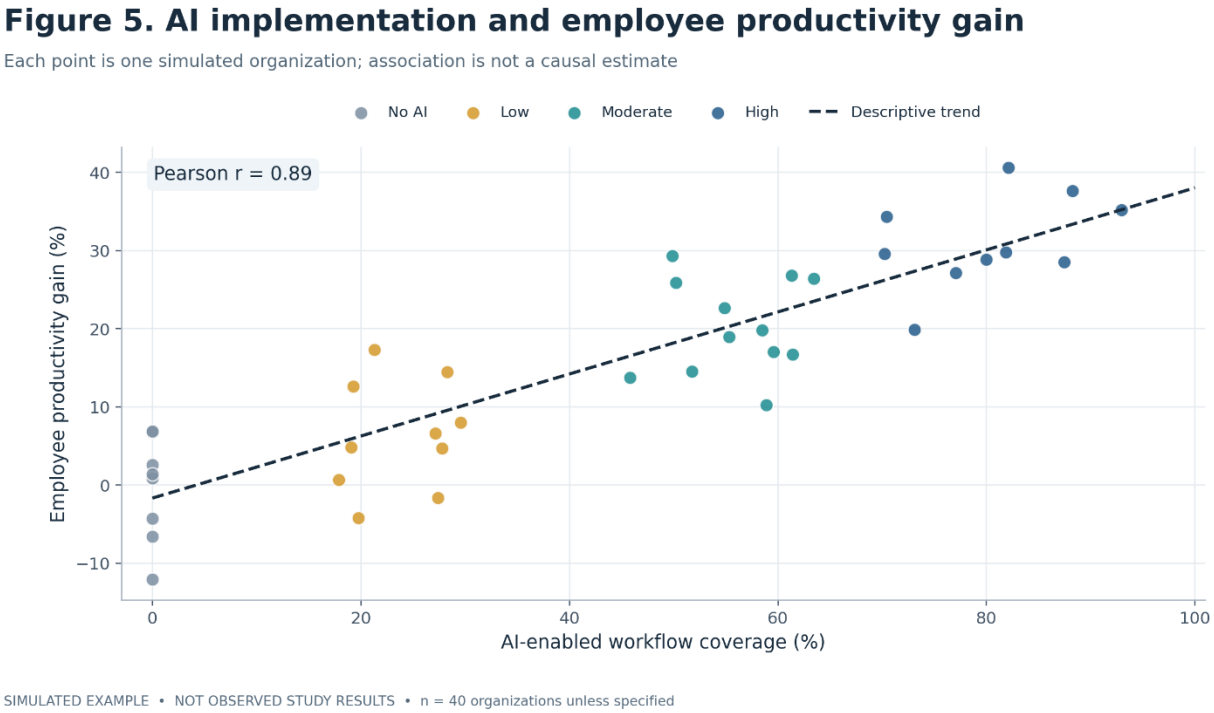


Figure 5. Relationship Between AI Implementation Intensity and Employee Productivity Improvement

Figure 5 shows the association between AI-based workflow coverage and the improvement in employee productivity in the 40 simulated organizations. The AI implementation strength is a measure based on the percentage of accounting processes assisted by AI and productivity improvement is the desired percentage change in the rate of completing tasks by employees. The scatter plot indicates that these variables have a high positive correlation with each other with a Pearson correlation coefficient of around 0.89. In the simulated dataset, organizations, where AI is implemented more, on average, experience more productivity improvements.

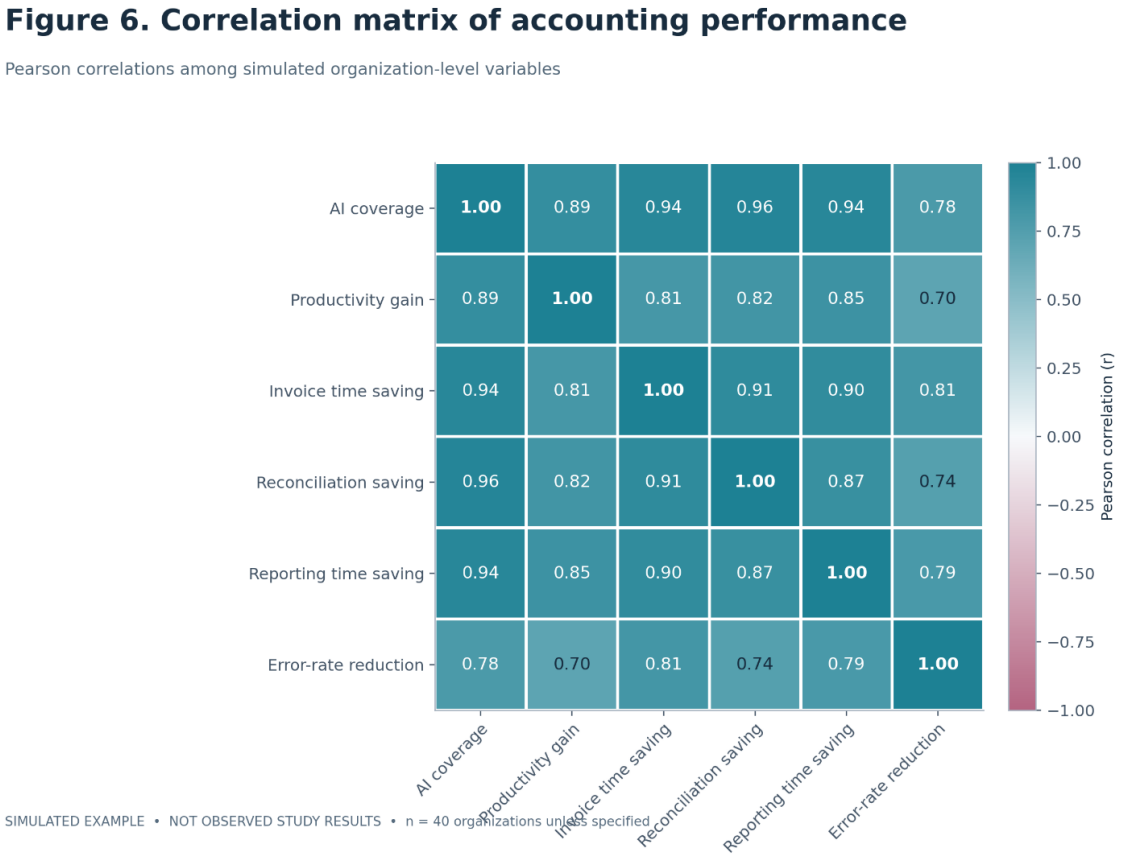


Figure 6. Correlation Matrix of AI Implementation, Employee Productivity, and Accounting Process Performance

The high intercorrelations also portray why multicollinearity has to be considered when many performance measures are incorporated as predictors in a regression model. The heatmap may be an informative visualization tool, but not a statistically significant setting in a real-population.

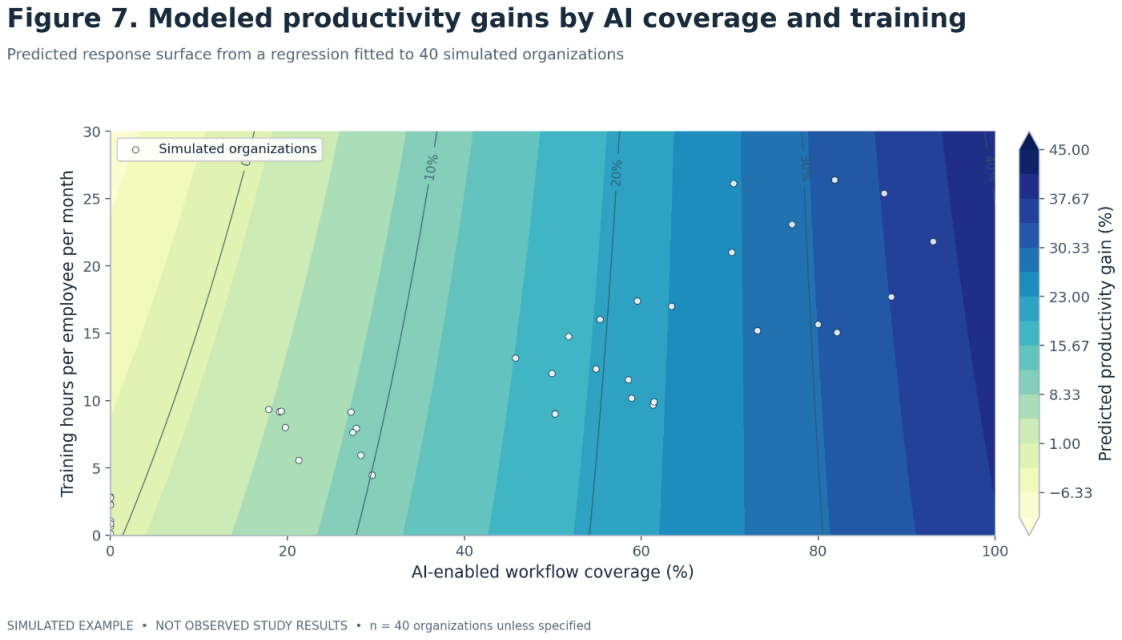


Figure 7. Modeled Effects of AI Workflow Coverage and Employee Training on Accounting Productivity Improvement

The percentage of the accounting processes that AI-based support takes place is displayed in the horizontal axis whereas the number of training hours of the AI-based activities per employee per month is shown on the vertical axis. The contour regions depict the predicted percentage of productivity improvement that are found in the simulated organization data based on a regression model fitted to that data. Throughout the modeled surface, there is a general indication that increased AI coverage, along with more intensive training of employees, correlates with increased productivity increments as predicted. This trend demonstrates that the significance of technological competence and organizational preparedness in helping AI be implemented might be significant. The number indicates that the training can enhance the strengths of employees to use smart applications in accounting and handle automatic workflow. The contour surface is however, not the actual outcomes of all the combinations of AI coverage and training, but is the predictions of the statistical models. Interpretations of predictions beyond the combinations observed should be viewed with care and the number does not show that employee training has a causal moderating effect on the productivity gains due to AI.

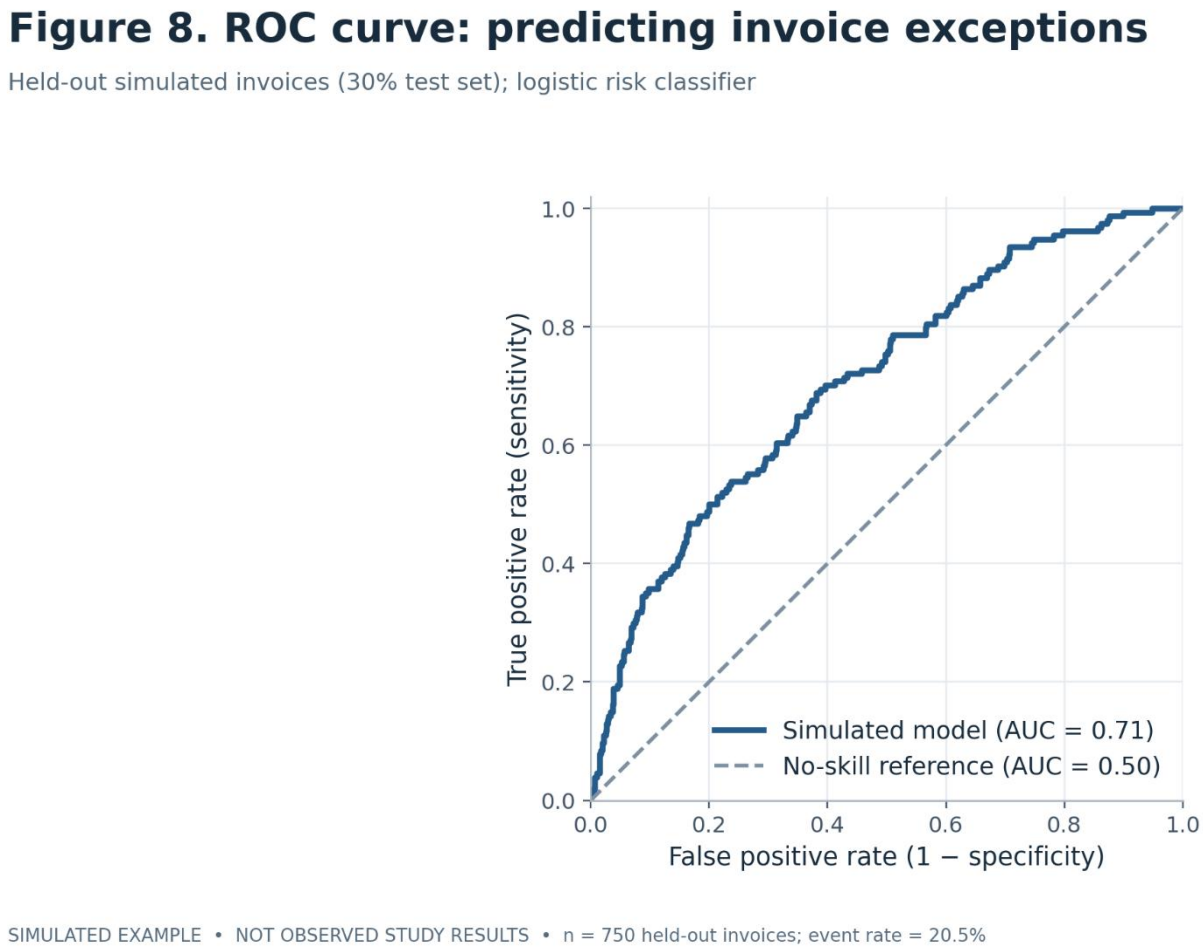


Figure 8. Receiver Operating Characteristic Curve for AI-Based Prediction of Invoice Processing Exceptions

Figure 8 shows the Receiver Operating Characteristic (ROC) curve of a simulated classification model to predict invoice-processing exceptions. Illustrative invoice attributes, such as document complexity, invoice amount, status of new vendor, and indicators of missing information are utilized in the model. It is tested on 750 held-out invoice records, which is 30% of the synthetic invoice data. The ROC curve demonstrates the amount of interrelation among the true positive rate (sensitivity) and other false positive rate (1 - specificity) at various classification thresholds. The simulated model has an Area Under the Curve (AUC) of about 0.71, which means it has moderate levels of discriminatory behavior in identifying invoices that need manual treatment. At AUC of 0.50 there would be an instance of random discrimination whereas AUC of 1.00 would mean perfect discrimination.

5. Discussion

5.1 Introduction

The main aspects of AI use are discussed in terms of possible effects on the accounting efficiency of organizations, how employees can complete their tasks, invoicing, financial reporting turnaround, transaction accuracy, and intelligent financial operations. Specific concern is the level of compliance between the illustrative relationships and earlier studies as well as the theoretical conceptualizations that underpin the proposed study.

5.2 Discussion of AI-Enabled Accounting Systems and Invoice Processing Efficiency

Figure 2 shows that there are differences in the invoice processing time prior to the adoption of AI and post-data collection in organizations with low and high implementation rates. Simulated outcomes indicate that with high AI adoption, there is a fluctuation in the mean time of invoice processing under about 12.10 to 7.82 minutes per invoice in the organization. This is a reflective decrease of about 35.4. Moderate adoption organisations show a decline in the number of minutes of 12.84 to 9.62 which translates to about 25.1 per cent. There is less reduction in the organization with low adoption by registering at 11.67 to 10.48, which is around 10.2 percent.

5.3 Discussion of AI Implementation and Financial Reporting Turnaround Time

In Figure 3, a simulated longitudinal comparison of the turnaround time of financial reporting after AI adoption versus organizations that did not implement AI was indicated. The exemplary findings suggest the reduction in the monthly financial closing time in high AI adoption organizations to about 7. 24 days post-implementation compared to 9. 70 months resulting prior to the implementation. This is equivalent to a decline in the number of days by about 2.46 days or 25.4 percent. Organizations that do not use AI, however, show considerably little change between 9.04 days to 8.90 days. This trend indicates that AI-based accounting systems can lead to efficiency in financial reporting by eliminating delays in recording transactions, reconcile accounts, verifying all transactions, and consolidating financial information.

5.4 Discussion of AI Adoption and Employee Productivity

In Figure 4, the distribution of rates of task completion by the employees of an accounting firm of 200 employees is modelled. The demonstrative data sets the average productivity rate of 6.66 accounting tasks per employee-hour, and the median of 6.55 accounting tasks per hour. The difference in productivity among the employees indicates that the individual outputs in accounting might vary as per the personal attributes, the complexity of the tasks involved, and the available organizational resources, and the level of technological support. Though the histogram cannot prove that an AI-related productivity effect is involved on its own, it helps to prove that it is vital to approach productivity as a quantifiable operational measure.

6. Conclusion

Artificially intelligent systems could also be utilized to assist workers reach peak productivity by classifying transactions and make documentuing that data simpler, automating time-consuming data-entry systems, and reducing the amount work-time it requires to perform a typical bookkeeping procedure.

6.1 Conclusion Regarding AI Adoption and Employee Productivity

The financial process efficiency is concerned with the speed, predictability, reliability of standard accounting operations and their resources efficiency. The analysis presented in illustration demonstrated shorter invoice processing times in the hypothetically designed organizations that were typified by increased AI introduction. It also had shown a slight enhancement in the turnaround time of financial reporting, and performance indicators in the reconciliation. Such trends are connected to the fact that it is expected that financial processes can be accelerated by using smart accounting applications that will automate document retrieval, document transactions documentation, data validation and data reconciliation. The processing of invoices is quite a current application, as it can be often connected with common administrative procedures.

6.2 Conclusion Regarding Financial Process Efficiency

Another major objective of the study was to investigate the relationship between AI implementation and financial process efficiency.

Financial process efficiency encompasses the speed, consistency, reliability, and resource effectiveness of routine accounting activities.

The illustrative analysis demonstrated shorter invoice processing times among hypothetical organizations with greater AI implementation intensity. It also showed improvements in financial reporting turnaround time and reconciliation-related performance indicators.

6.3 Conclusion Regarding Accounting Accuracy and Financial Reporting Quality

Accounting accuracy is an essential consideration when evaluating AI-enabled accounting technologies because financial information must remain reliable, complete, and consistent with applicable reporting requirements.

Although AI systems may improve processing speed and reduce repetitive employee involvement, such benefits should not be achieved at the expense of accounting accuracy or internal control effectiveness.

6.4 Conclusion Regarding Employee Training and Human–AI Collaboration

The study also examined the potential importance of employee training and technological competence in influencing AI-related accounting performance.

The illustrative contour analysis suggested that productivity improvements may be greater when extensive AI implementation is combined with adequate employee training.

Credit authorship contribution statement

Zain Ul Abedin: Writing – original draft, Formal analysis, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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