ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 10| Issue: 11| November 2024|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2024: 8.402|| ISI Value: 1.188

BENEFITS OF AI ADOPTION IN ACCOUNTING INFORMATION SYSTEMS: PERSPECTIVES FROM INDIAN ACCOUNTING PROFESSIONALS

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Article DOI: https://doi.org/10.36713/epra19044
DOI No: 10.36713/epra19044

ABSTRACT
Purpose*: This study examines the benefits of AI in accounting, focusing on work efficiency, data quality, and financial management effectiveness, and explores demographic influences on AI familiarity.*
Methodology*: Descriptive, correlation, and regression analyses were conducted using data from 83 accounting professionals.*
Findings*: AI is perceived to enhance efficiency, data quality, and reduce workload. Significant findings include a negative correlation between age and AI familiarity, while education did not show a significant relationship. Only financial reporting tasks showed a marginal impact on data quality.*
Practical Implications*: The study provides insights into AI's role in accounting and highlights the need for strategic implementation and training.*
Originality/Value*: This research enhances understanding of AI's integration into accounting practices and demographic impacts.*
KEYWORDS: *Artificial Intelligence (AI), Accounting Information System, Benefits, Accounting technology*

1. INTRODUCTION

The integration of Artificial Intelligence (AI) into accounting marks a pivotal transformation in modern financial practices, reshaping the landscape of decision-making, auditing, and financial management. As businesses strive to adapt to a rapidly digitalizing world, AI has emerged as a critical tool, allowing accounting professionals to manage increasing complexities with greater efficiency and accuracy (Zhang et al., 2020).

Historically, accounting has evolved through generations of technological innovations, from the use of abacuses and double-entry bookkeeping to advanced computerized accounting systems. The current wave of AI technologies, including machine learning, robotic process automation, and data analytics, represents a continuation of this trend, fundamentally altering the traditional roles of accountants (Akhter & Sultana, 2018). AI-powered tools augment human expertise by streamlining workflows, enhancing financial reporting accuracy, and uncovering strategic insights that were previously inaccessible (Kroon et al., 2021). The ability to process vast volumes of data at unprecedented speeds signals a profound shift from manual tasks to a more data-driven and analytical approach (Zhang et al., 2020)

Moreover, the increasing reliance on AI-driven automation reflects the rising importance of technological proficiency for accounting professionals. As AI takes over repetitive and rule-based tasks, accountants are now required to develop skills that blend financial acumen with technological expertise, ensuring they remain relevant in an industry undergoing rapid transformation (Akhter & Sultana, 2018). AI adoption has become essential, not only for increasing operational efficiency but also for responding to growing data volumes, regulatory complexity, and the demand for real-time insights (Hasan, 2022).

The significance of this technological shift extends beyond automation. AI adoption in accounting is closely linked to the broader integration of emerging technologies such as blockchain, particularly among small and medium enterprises (SMEs) (Polas et al., 2022). These technologies are transforming financial operations by improving transparency, reducing errors, and enhancing decision-making processes. Despite the clear advantages, the adoption of AI is not uniform across regions and firm sizes. Larger firms in developed countries, such as the United States and the United Kingdom, have been quicker to embrace AI technologies, while smaller firms and those in emerging economies face barriers such as cost, lack of resources, and limited awareness (Luo et al., 2018). The historical trajectory of technology in accounting serves as a critical backdrop to this transformation. From manual ledger entries to the current state of AI integration, the evolution of accounting processes reveals a continuous push toward innovation and optimization (Hasan, 2022). AI is not only revolutionizing the industry but also challenging traditional skillsets, as professionals must now balance advanced technical knowledge with critical thinking and strategic analysis (Akhter & Sultana, 2018).

Despite its promises, AI's integration into accounting also presents challenges. Concerns about data security, job displacement, and the need for upskilling loom large as professionals navigate this shift (Yanling Shi, 2019). Addressing these concerns will require a multifaceted approach that includes the development of clear ethical guidelines, ensuring robust data privacy measures, and rethinking the educational curriculum to prepare future accountants for a world driven by AI (Cindy L. Greenman, 2017).

2. LITERATURE REVIEW

In *Riding the Waves of Artificial Intelligence in Advancing Accounting and Its Implications for Sustainable Development Goals* (Peng et al., 2023) explore the transformative role of AI in accounting, focusing on how AI-driven efficiency and real-time data analysis can streamline operations and support Sustainable Development Goals (SDGs). By automating repetitive tasks, AI reduces resource consumption and enhances accuracy, thereby fostering sustainable practices within organizations and promoting economic growth aligned with SDG objectives.(Peng et al., 2023).

Kureljusic and Karger, in *Forecasting in Financial Accounting with Artificial Intelligence* (2023), investigate the use of AI for improving accuracy in financial forecasting. They highlight AI's ability to predict financial trends and identify risks such as bankruptcy, while noting challenges in integrating AI with traditional forecasting models. The authors suggest that further research should focus on the sociotechnical aspects of AI to better understand and implement these technologies within accounting(Kureljusic & Karger, 2023).

In their study *Usage and Impact of Artificial Intelligence on Accounting: Evidence from Malaysian Organisations* (2020), Lee and Tajudeen analyze the implementation of AI in Malaysian accounting firms. They report that AI tools enhance productivity, especially in tasks like invoice processing and risk assessment, although adoption remains low due to cost and limited awareness. The study emphasizes the importance of AI integration in Malaysia's accounting industry to align with global trends (Lee & Tajudeen, 2020).

Losbichler and Lehner discuss the limitations of AI in *Limits of Artificial Intelligence in Controlling and the Ways Forward: A Call for Future Accounting Research* (2021), particularly in complex decision-making processes. They argue that while AI is effective in automating routine tasks, its efficacy in nuanced decision-making is constrained. They advocate for a research focus on collaborative models where human expertise complements AI in tackling sophisticated accounting challenges (Losbichler & Lehner, 2021).

Vărzaru's *Assessing Artificial Intelligence Technology Acceptance in Managerial Accounting* (2022) examines AI adoption in Romanian managerial accounting, identifying resistance to change and job security concerns as primary barriers. Vărzaru suggests that increasing educational programs and skill development can help bridge the acceptance gap, making AI adoption smoother and more effective in managerial decision-making (Vărzaru, 2022).

Bako and Tanko, in *The Place of Artificial Intelligence in Accounting Field and the Future of Accounting Profession* (2022), discuss AI's potential to streamline accounting processes while asserting that human judgment remains essential. They highlight the need for accountants to upskill in digital technologies and recommend that academic curricula evolve to include AI to better prepare future professionals (Bako & Tanko, 2022).

In *The Interest, Knowledge, and Usage of Artificial Intelligence in Accounting: Evidence from Accounting Professionals* (2021), Johnson et al. examine how accounting professionals perceive AI. Their findings show that while there is high interest in AI, actual implementation remains limited. They suggest that increasing familiarity and practical exposure to AI among accountants could facilitate its broader integration, especially as professionals recognize AI's potential to enhance accuracy and efficiency (Johnson et al., 2021).

Li and Zheng, in *The Impact of Artificial Intelligence on Accounting* (2018), explore how AI can mitigate financial fraud by implementing automated checks and balances, especially in small and medium-sized enterprises. They argue that AI's role in improving the quality of accounting information is substantial, as it can reduce human error and enhance data reliability through automation. The authors assert that AI's role in fraud prevention and data accuracy is pivotal in modernizing the accounting industry (Li & Zheng, 2018).

Zhang et al., in *The Impact of Artificial Intelligence and Blockchain on the Accounting Profession* (2020), assess the influence of AI and blockchain on the future of accounting. They highlight the capabilities of AI in automating data recognition, invoice processing, and report generation, which reduces dependency on basic accounting roles. The study also explores blockchain's role in secure data verification, which can aid in preventing fraud and improving the reliability of financial records. The authors recommend that educational institutions incorporate these technologies into curricula to prepare future accountants for a technologically advanced industry (Zhang et al., 2020).

3. RESEARCH METHODOLOGY

3.1. Research Questions

The study addresses the following research questions:

1. What is the relationship between experience in the accounting profession and belief in AI adoption?
2. How does familiarity with AI influence belief in AI adoption?
3. What is the impact of demographic factors (age, gender, education) on belief in AI adoption?

3.2. Research Aim

The primary aim of this research is to investigate the relationship between accounting professionals' experience, familiarity with AI, current AI usage, and demographic factors, and their belief in the adoption of AI in accounting practices.

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Additionally, the study examines the correlation between education level and familiarity with AI, as well as the benefits perceived from using AI for specific accounting tasks.

3.3. Research Objectives

The study was conducted with the following key objectives:

1. To assess the impact of experience in the accounting profession on the belief in AI adoption.
2. To examine the relationship between familiarity with AI and the belief in its adoption in accounting practices.
3. To determine the influence of current AI usage on the belief in AI adoption.
4. To analyze the effect of demographic factors such as age, gender, and education on the belief in AI adoption.
5. To investigate the correlation between education qualifications and familiarity with AI among accounting professionals.
6. To evaluate the association between specific accounting tasks performed using AI and the reported benefits of AI usage.
7. To study the correlation between age and familiarity with AI among accounting professionals.

3.4. Sampling Design

The study used data collected from 102 accounting professionals through a survey. A non-probability sampling method was employed, where participants were selected based on their willingness to participate and their relevance to the study. This method ensured the inclusion of a diverse range of accounting professionals with varying experience, familiarity, and use of AI in accounting practices.

3.5. Sources of Data

Primary data were collected through a structured questionnaire distributed to accounting professionals using survey. The questionnaire focused on collecting information regarding experience, familiarity, and usage of AI in accounting, as well as demographic details. Secondary data were obtained from existing literature on AI adoption in accounting practices.

3.6. Research Tools

The following statistical tests and data management tools were used for the analysis: I. Mean and paired t-test for comparing variables. II. Data management software, including Jamovi, SPSS, and MS Excel, were used for statistical analysis and data handling.

3.7. Limitations of the Study

The study faced certain limitations:

1. The geographic focus on Indian professionals may limit the relevance of the findings in an international context.
2. Rapid technological advancements in AI may render some findings less applicable in future scenarios.

4. DATA ANALYSIS AND FINDINGS

4.1. Reported Benefits of AI Usage:

Descriptive Statistics

	Minimum	Maximum	Mean	Std. Deviation
Improved the work efficiency	1	5	4.06	0.966
Improved the Time efficiency.	1	5	3.94	1.345
Improved the quality of our accounting information.	1	5	3.76	1.200
Improved the effectiveness of financial data.	1	5	3.82	1.074
Reduced work load	1	5	3.82	1.237

Table 1

Descriptive statistics were calculated to examine the reported benefits of artificial intelligence (AI) usage in the organization. To assess the perceived benefits of AI in work efficiency, time efficiency, quality, and workload, descriptive statistics showed that 'Improved work efficiency' had a mean of 4.06 (SD = 0.966) on a 5-point scale, indicating a positive perception among respondents. 'Time efficiency' followed with a mean of 3.94 (SD = 1.345), reflecting moderate variability in responses

4.2. Usage of Various AI Tools Among Accounting Professionals

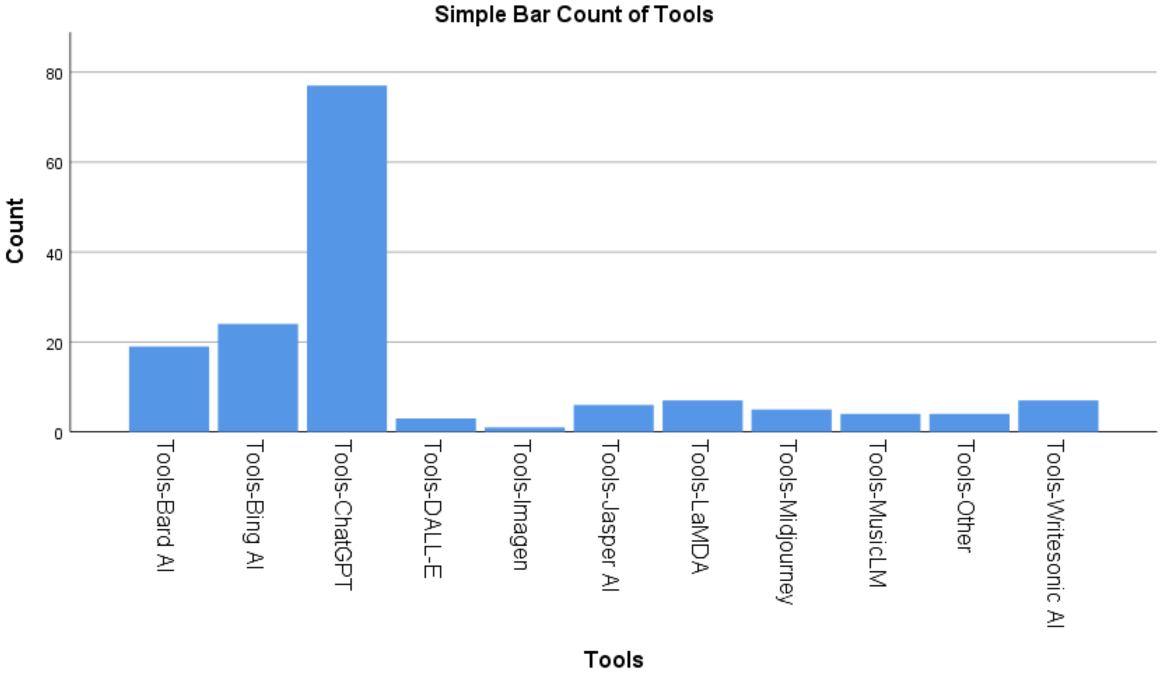

Chart 1

Among the listed AI tools, "ChatGPT" has the highest mean usage score of 0.93, suggesting that it is the most frequently used tool among the respondents, with a relatively low standard deviation of 0.261.

In contrast, "Bard AI" has a mean usage score of 0.23, with a higher standard deviation of 0.423, suggesting more variability in its usage among respondents.

"Midjourney" and "DALL-E" have mean scores of 0.06 and 0.04, respectively, with relatively low standard deviations, indicating less frequent usage compared to other tools.

4.3. Hypothesis 1:

H0: There is no significant relationship between experience in the accounting profession and belief in AI adoption.
H1: There is a significant relationship between experience in the accounting profession and belief in AI adoption.

		Do you believe that AI should be used in the field of accounting?
What is your experience in accounting profession?	Correlation Coefficient	-0.163
	Sig. (2-tailed)	0.14
	N	83
	Sig. (2-tailed)	.

Table 2

To investigate the relationship between experience in the accounting profession and belief in AI adoption, a Spearman's rho correlation was calculated.

The correlation coefficient between experience in the accounting profession and belief in AI adoption was found to be -.163, indicating a weak negative correlation. However, the correlation was not statistically significant (p = .140, 2-tailed).

This result suggests that there is no significant relationship between experience in the accounting profession and belief in AI adoption among the participants.

4.4. Hypothesis 2

H0: There is no significant relationship between familiarity with AI and belief in AI adoption.
H1: There is a significant relationship between familiarity with AI and belief in AI adoption.

		Do you believe that AI should be used in the field of accounting?
How familiar are you with artificial intelligence (AI)? [Familiarity]	Correlation Coefficient	0.195
	Sig. (2-tailed)	0.078
	N	83

Table 3

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A Spearman's rho correlation was conducted to investigate the relationship between familiarity with artificial intelligence (AI) and belief in AI adoption among the participants.

The correlation coefficient between familiarity with AI and belief in AI adoption was found to be 0.195, indicating a weak positive correlation. However, the correlation did not reach statistical significance (p = 0.078, 2-tailed).

Based on the data, there is no significant relationship between familiarity with AI and belief in AI adoption among the participants. This suggests that greater familiarity with AI may slightly increase the belief in its adoption.

4.5. Hypothesis 3

H0: There is no significant relationship between current AI usage and belief in AI adoption.
H1: There is a significant relationship between current AI usage and belief in AI adoption

	Are you currently using AI in your daily tasks?	N	Mean	Std. Deviation	Std. Error Mean
Do you believe that AI should be used in the field of accounting?	Yes	29	2.76	.577	.107
	N0	54	2.33	.752	.102

Table 4

		t-test for Equality of Means					
		F	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Do you believe that AI should be used in the field of accounting?	Equal variances assumed	10.211	2.652	81	0.01	0.425	0.16
	Equal variances not assumed		2.871	71.172	0.005	0.425	0.148

Table 5

To test the hypothesis regarding the relationship between current AI usage and belief in AI adoption, an independent samples t-test was conducted. The analysis involved comparing the mean belief in AI adoption scores between respondents who are currently using AI in their daily tasks and those who are not.

Group statistics revealed that the mean belief in AI adoption score for participants currently using AI (M = 2.76, SD = 0.577) was higher than for those not currently using AI (M = 2.33, SD = 0.752).

The assumption of equal variances was violated (Levene's test: F = 10.211, p = 0.002), suggesting unequal variances between the two groups. Therefore, the t-test assuming unequal variances was reported.

The t-test results indicated a significant difference in mean belief in AI adoption scores between the two groups (t(71.172) = 2.871, p = 0.005). The mean difference in belief in AI adoption scores was 0.425, with a standard error of 0.148.

The 95% confidence interval for the difference in means ranged from 0.130 to 0.721. This suggests that participants currently using AI in their daily tasks tend to have a significantly higher belief in AI adoption compared to those not using AI.

4.6. Hypothesis 4:

H0: There is no significant association between demographic factors (age, gender, education) and belief in AI adoption.
H1: There is a significant association between demographic factors (age, gender, education) and belief in AI adoption.

Age

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	46.222[a]	12	.000
Likelihood Ratio	44.604	12	.000
Linear-by-Linear Association	6.232	1	.013
N of Valid Cases	83		

Table 6

A cross-tabulation was conducted to examine the association between age and belief in AI adoption among respondents. The analysis included data from 83 participants.

The cross-tabulation revealed varying belief in AI adoption across different age groups. Among respondents aged 20-25 years, 18 believed AI should be used in accounting, while 4 did

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not and 6 were unsure. In contrast, among respondents aged 25-30 years, the majority (23) believed in AI adoption, with fewer (2) expressing uncertainty and only 2 opposing AI adoption.

A chi-square test was performed to determine the association between age and belief in AI adoption. The results indicated a significant association ($\chi^2(12) = 46.222$, $p < .001$), suggesting that age is significantly associated with belief in AI adoption among the participants.

Gender

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	2.055[a]	2	.358
Likelihood Ratio	2.010	2	.366
Linear-by-Linear Association	.097	1	.756
N of Valid Cases	83		

Table 7

Another cross-tabulation was conducted to explore the association between gender and belief in AI adoption. The analysis included data from 83 respondents.

The cross-tabulation revealed that both male and female respondents had varying beliefs in AI adoption. Among males, 35 believed AI should be used in accounting, while among females, 16 held the same belief. Similarly, there were variations in the "maybe" and "no" categories.

A chi-square test was conducted to assess the association between gender and belief in AI adoption. The results indicated no significant association between gender and belief in AI adoption ($\chi^2(2) = 2.055$, $p = .358$).

Education Qualification

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	14.961[a]	6	.021
Likelihood Ratio	15.016	6	.020
Linear-by-Linear Association	.428	1	.513
N of Valid Cases	83		

Table 8

A third cross-tabulation was performed to investigate the association between education qualification and belief in AI adoption. The analysis involved data from 83 participants.

The cross-tabulation displayed differing beliefs in AI adoption across different education qualifications. For example, among respondents with post-graduation qualifications, 25 believed AI should be used in accounting, while only 3 opposed it.

A chi-square test was conducted to examine the association between education qualification and belief in AI adoption. The results indicated a significant association ($\chi^2(6) = 14.961$, $p = .021$), suggesting that education qualification is significantly associated with belief in AI adoption among the participants.

4.7. Hypothesis 5

H0: There is no significant correlation between education qualification and familiarity with AI among accounting professionals.
H1: There is a significant correlation between education qualification and familiarity with AI among accounting professionals.

		Education Qualification
How familiar are you with artificial intelligence (AI)? [Familiarity]	Pearson Correlation	-.051
	Sig. (2-tailed)	.648
	N	83

Table 9

To test the hypothesis regarding the correlation between education qualification and familiarity with artificial intelligence (AI), a Pearson correlation coefficient was calculated. The analysis included data from 83 respondents.

The Pearson correlation coefficient between education qualification and familiarity with AI was found to be -0.051. This indicates a very weak negative correlation between the two variables. However, the correlation was not statistically significant ($p = 0.648$, 2-tailed).

Based on the data, there is no significant correlation between education qualification and familiarity with AI among accounting professionals.

4.8. Hypothesis 6:

H0: There is no significant association between specific accounting tasks using AI and reported benefits of AI usage.
H1: There is a significant association between specific accounting tasks using AI and reported benefits of AI usage.

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Improved Work Efficiency

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.457	5	1.091	1.266	.345[b]
	Residual	9.484	11	.862		
	Total	14.941	16			

Table 10

a. Dependent Variable: Improved the work efficiency

b. Predictors: (Constant), Task-Auditing, Task-Tax preparation, Task-Payroll, Task-Financial reporting, Task-Bookkeeping

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.890	.601		6.474	.000
	Task-Bookkeeping	-.637	.605	-.310	-1.052	.315
	Task-Payroll	.705	.518	.343	1.361	.201
	Task-Financial reporting	.322	.506	.172	.636	.538
	Task-Tax preparation	.503	.613	.227	.821	.429
	Task-Auditing	.300	.545	.160	.551	.593

Table 11

a. Dependent Variable: Improved the work efficiency

The regression analysis for improved work efficiency revealed a nonsignificant relationship ($F(5,11) = 1.266$, $p = .345$) between specific accounting tasks using AI and reported benefits. None of the specific accounting tasks showed a significant effect on improved work efficiency.

Improved Time Efficiency

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.162	5	.832	.369	.859[b]
	Residual	24.780	11	2.253		
	Total	28.941	16			

Table 13

a. Dependent Variable: Improved the Time efficiency.

b. Predictors: (Constant), Task-Auditing, Task-Tax preparation, Task-Payroll, Task-Financial reporting, Task-Bookkeeping

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.526	.971		3.631	.004
	Task-Bookkeeping	-.114	.978	-.040	-.117	.909
	Task-Payroll	.433	.837	.151	.516	.616
	Task-Financial reporting	.686	.819	.262	.838	.420
	Task-Tax preparation	.412	.990	.134	.416	.685
	Task-Auditing	-.109	.881	-.042	-.124	.904

Table 14

a. Dependent Variable: Improved the Time efficiency.

For improved time efficiency, the regression analysis showed no significant relationship ($F(5,11) = 0.369$, $p = .859$) between specific accounting tasks using AI and reported benefits. None of the specific accounting tasks significantly influenced improved time efficiency.

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Improved Quality of Accounting Information:

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.725	5	2.545	2.709	.078[b]
	Residual	10.333	11	.939		
	Total	23.059	16			

Table 15

a. Dependent Variable: Improved the quality of our accounting information.

b. Predictors: (Constant), Task-Auditing, Task-Tax preparation, Task-Payroll, Task-Financial reporting, Task-Bookkeeping

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.152	.627		5.025	.000
	Task-Bookkeeping	-.530	.632	-.207	-.839	.419
	Task-Payroll	1.030	.541	.403	1.905	.083
	Task-Financial reporting	1.182	.529	.506	2.235	.047
	Task-Tax preparation	.121	.639	.044	.190	.853
	Task-Auditing	.212	.569	.091	.373	.716

Table 16

a. Dependent Variable: Improved the quality of our accounting information.

The regression analysis for improved quality of accounting information indicated a marginally significant relationship (F(5,11) = 2.709, p = .078) between specific accounting tasks using AI and reported benefits. However, only the task of financial reporting showed a significant effect on improving the quality of accounting information (β = .506, p = .047).

Improved Effectiveness of Financial Data:

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.325	5	1.465	1.446	.283[b]
	Residual	11.145	11	1.013		
	Total	18.471	16			

Table 17

a. Dependent Variable: Improved the effectiveness of financial data.

b. Predictors: (Constant), Task-Auditing, Task-Tax preparation, Task-Payroll, Task-Financial reporting, Task-Bookkeeping

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.291	.651		5.052	.000
	Task-Bookkeeping	-.335	.656	-.147	-.511	.619
	Task-Payroll	1.040	.562	.455	1.852	.091
	Task-Financial reporting	.512	.549	.245	.933	.371
	Task-Tax preparation	.205	.664	.084	.309	.763
	Task-Auditing	.371	.591	.177	.627	.543

Table 18

a. Dependent Variable: Improved the effectiveness of financial data.

For improved effectiveness of financial data, the regression analysis revealed no significant relationship (F(5,11) = 1.446, p = .283) between specific accounting tasks using AI and reported benefits. None of the specific accounting tasks significantly influenced the effectiveness of financial data.

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Reduced Workload

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.848	5	.970	.544	.740[b]
	Residual	19.623	11	1.784		
	Total	24.471	16			

Table 19

a. Dependent Variable: Reduced work load

b. Predictors: (Constant), Task-Auditing, Task-Tax preparation, Task-Payroll, Task-Financial reporting, Task-Bookkeeping

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.518	.864		4.070	.002
	Task-Bookkeeping	-.131	.871	-.050	-.150	.883
	Task-Payroll	1.085	.745	.412	1.457	.173
	Task-Financial reporting	-.215	.729	-.089	-.295	.774
	Task-Tax preparation	.387	.881	.137	.439	.669
	Task-Auditing	.189	.784	.079	.241	.814

Table 20

a. Dependent Variable: Reduced work load

The regression analysis for reduced workload demonstrated no significant relationship ($F(5,11) = 0.544$, $p = .740$) between specific accounting tasks using AI and reported benefits. None of the specific accounting tasks significantly influenced reduced workload.

4.9. Hypothesis 7

H0: There is no significant correlation between age and familiarity with artificial intelligence (AI) among accounting professionals.

H1: There is a significant correlation between age and familiarity with artificial intelligence (AI) among accounting professionals.

		Age
How familiar are you with artificial intelligence (AI)? [Familiarity]	Pearson Correlation	-.294**
	Sig. (2-tailed)	.007
	N	83

Table 21

A Pearson correlation coefficient was calculated to examine the relationship between age and familiarity with AI among accounting professionals. The analysis included data from 83 respondents.

The Pearson correlation coefficient between age and familiarity with AI was found to be -0.294, which is significant at the 0.01 level (2-tailed), suggesting a moderately strong negative correlation. This suggests that as age increases, familiarity with AI tends to decrease among accounting professionals.

CONCLUSION

This study thoroughly examined the perceived benefits of artificial intelligence (AI) in accounting and its potential impact on work efficiency, data quality, and overall effectiveness of financial management. Through descriptive analysis, it was observed that AI adoption is widely believed to enhance work and time efficiency, improve the accuracy and quality of accounting information, increase the effectiveness of financial data processing, and reduce the workload of accounting professionals. The results underscore the growing recognition of AI's positive role in transforming the accounting landscape. Despite initial skepticism among some practitioners, AI is increasingly seen as a tool that can streamline tasks, enabling accountants to focus more on strategic decision-making rather than routine work.

The correlation analysis provided key insights into the demographic and professional factors that influence AI adoption. Interestingly, no significant relationship was found between the level of experience in accounting and belief in AI adoption, or between familiarity with AI and its adoption, suggesting that experience or familiarity alone does not determine one's openness to AI integration. However, there was a significant association between current AI usage and belief in AI adoption, highlighting that those already using AI tools are more likely to support their broader implementation. Demographic factors such as age and education were also significantly associated with the belief in AI adoption, suggesting that younger, more educated professionals are more inclined to see the value of AI in accounting. Gender, however, did not show a significant impact, reflecting the growing inclusivity of AI perceptions across the professional spectrum. In conclusion, AI adoption in accounting is shaped by various factors, and its potential to revolutionize the profession continues to gain recognition among accounting professionals.

Future Scope

Future research can explore the impact of AI on specific accounting tasks in more depth, particularly how emerging AI tools might further enhance accounting efficiency. Expanding the sample size and focusing on industry-specific AI applications could also yield deeper insights into the evolving role of AI in professional accounting practices.

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