

Level of Acceptance and Behavioral Intention on the Use of Artificial Intelligence in Internal Audit Procedure

Xiaoyu Chen

Graduate School of Business Management and Education, Philippine Christian University, Manila, Philippines

ABSTRACT

The integration of Artificial Intelligence (AI) into internal auditing is reshaping conventional audit methodologies by enhancing precision, efficiency, and analytical capacity. Despite its growing relevance, the degree to which internal auditors accept and intend to adopt AI technologies remains insufficiently examined. This study investigated the level of acceptance and behavioral intention among accounting professionals toward AI adoption in auditing, guided by the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Utilizing a descriptive-correlational research design, data were gathered from 431 accounting professionals selected through stratified random sampling. The research instrument assessed acceptance across four UTAUT constructs—Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—and evaluated respondents' behavioral intention to adopt AI tools. Results indicated generally high acceptance levels, with Performance Expectancy and Effort Expectancy emerging as key drivers. Significant differences in acceptance and intention were observed based on demographic variables such as age, job position, and AI familiarity. Furthermore, strong positive correlations were found between all acceptance constructs and behavioral intention. The study recommends targeted capacity-building initiatives and improved organizational infrastructure to facilitate successful AI integration. These findings provide valuable insights into the human and organizational dynamics influencing AI adoption in internal audit contexts and inform strategic planning for technology-driven transformation in the profession.

KEYWORDS

Artificial Intelligence; Internal Auditing; Behavioral Intention; Acceptance; UTAUT

1. INTRODUCTION

Artificial Intelligence (AI) is transforming the accounting and auditing landscape by automating routine tasks, enhancing data analysis, and increasing overall audit accuracy and efficiency. It enables auditors to detect anomalies, assess risks, and generate insights with unprecedented speed and precision (Abdullah and Almaqtari, 2024; Iwuanyanwu et al., 2023). Technologies such as machine learning, natural language processing, and robotic process automation are now being integrated into audit tools, shifting the auditor's role from data verification to strategic interpretation (Seethamraju and Hecimovic, 2023).

Despite its benefits, AI adoption in auditing is not solely a technological issue—it is equally a human and organizational challenge. The level of acceptance and behavioral intention among auditors plays a pivotal role in the success of AI implementation (Cao et al., 2021). Factors such as perceived usefulness, ease of use, peer influence, and infrastructure support influence an individual's readiness to adopt new technologies, as explained by the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Liu and Zhang, 2024; Alghatrifi and Khalid, 2019).

There is growing literature on AI capabilities and impacts in the broader financial services sector; however, studies focusing specifically on internal auditors' psychological and behavioral responses to AI remain limited (Albawwat and Frijat, 2021). Auditors may perceive AI as either a complement to their work or a disruptive force threatening job security or professional judgment. Thus, understanding the interplay between technological potential and human receptiveness is critical.

This study investigates the acceptance and behavioral intention of accounting professionals regarding AI integration in internal auditing, using the UTAUT model as a theoretical lens. It aims to provide empirical insights that can guide policy makers, audit firms, and professional bodies in designing effective AI adoption strategies. Specifically, the study answers the following questions:

- (1) What is the level of acceptance of AI in terms of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions?
- (2) What is the behavioral intention of auditors to adopt AI in audit procedures?
- (3) Are there significant differences in acceptance and behavioral intention based on respondents' profiles?
- (4) Is there a significant relationship between the level of acceptance and behavioral intention to use AI?
- (5) What action plan can be proposed based on the findings?

2. METHODS

This study employed a quantitative descriptive-correlational research design to measure both the current perceptions of internal auditors and the relationships among variables related to AI acceptance and behavioral intention. The design was appropriate for capturing the multifaceted attitudes of professionals toward AI tools and for analyzing whether these perceptions were influenced by demographic and professional factors.

The target population included approximately 5,000 accounting professionals involved in internal auditing roles, either in public or private organizations. Using the Raosoft sample size calculator, a sample size of 431 respondents was established to ensure statistical representativeness, based on a 5% margin of error and 95% confidence level. A stratified random sampling method was employed to ensure representation across variables such as job position, length of experience, and familiarity with AI technologies. Inclusion criteria required participants to have a minimum of one year of auditing experience and a basic understanding of AI-related tools or concepts.

The primary instrument was a structured questionnaire, consisting of three parts.

- (1) Part I gathered demographic and professional information, including age, gender, job title, years of experience, and level of familiarity with AI in auditing.
- (2) Part II measured acceptance of AI using the four UTAUT constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. Each construct was assessed using seven items on a 4-point Likert scale (1 = Strongly Disagree to 4 = Strongly Agree).
- (3) Part III evaluated Behavioral Intention to adopt AI, using seven items rated on the same scale.

The survey instrument underwent rigorous content validation by a panel of five subject-matter experts specializing in internal auditing, artificial intelligence applications in accounting, and quantitative educational assessment. Following validation, a pilot test with 40 accounting professionals was conducted to assess instrument reliability, with Cronbach's Alpha coefficients ranging from 0.881 to 0.940 across all UTAUT constructs and the behavioral intention scale, demonstrating excellent internal consistency.

Data were processed and analyzed using SPSS Version 26. Descriptive statistics (frequency, percentage, mean) were used to summarize the data. To test relationships and group differences, inferential statistical tools were applied. The Shapiro-Wilk test revealed that the data were not normally distributed ($p < 0.05$), prompting the use of non-parametric tests:

- (1) The Kruskal-Wallis test assessed differences across demographic groups.
- (2) The Spearman’s Rho correlation determined the strength of relationships between the UTAUT constructs and behavioral intention.

3. RESULTS

Table 1. Level of Acceptance of AI in Auditing

Construct	Composite Mean	Interpretation
Performance Expectancy	2.66	Agree
Effort Expectancy	2.69	Agree
Social Influence	2.69	Agree
Facilitating Conditions	2.69	Agree

Legend: 3.50–4.00 = Strongly Agree; 2.50–3.49 = Agree; 1.50–2.49 = Disagree; 0–1.49 = Strongly Disagree

Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—respondents demonstrated a general agreement on the relevance and potential of AI in auditing, with a uniform composite mean of 2.69 for three of the four dimensions. This consistency suggests that accounting professionals view AI as beneficial, manageable, socially supported, and institutionally backed. Notably, Performance Expectancy scored slightly lower at 2.66, indicating a slightly less optimistic view regarding AI’s ability to enhance job performance compared to other acceptance areas.

The similar mean values across constructs point to a balanced perception among auditors, where no particular barrier stands out as dominant. However, these scores also indicate a moderate level of acceptance—suggesting that while respondents are open to AI use, they are not overwhelmingly convinced.

Table 2. Behavioral Intention to Use AI in Auditing

Statement	Mean	Std. Dev	Interpretation
I would allocate time to attend workshops or training on AI	2.77	1.00	Agree
I believe AI will become essential in auditing soon	2.75	0.98	Agree
I plan to recommend AI tools to colleagues	2.73	0.99	Agree
I am willing to learn more about AI to improve my auditing skills	2.71	1.04	Agree
I would frequently use AI tools if available	2.69	0.98	Agree
I intend to use AI tools in my auditing tasks within the next year	2.68	1.02	Agree
I am committed to exploring how AI can transform my auditing processes	2.68	0.98	Agree
Composite Mean	2.72	0.90	Agree

Legend: 3.50–4.00 = Strongly Agree; 2.50–3.49 = Agree; 1.50–2.49 = Disagree; 0–1.49 = Strongly Disagree

The overall mean behavioral intention score was 2.72, with respondents agreeing that they are willing to engage with AI through training, application, and advocacy. The highest-rated item was the willingness to attend workshops ($M = 2.77$), followed by the belief that AI will soon become essential in auditing ($M = 2.75$). These findings imply a forward-looking mindset, where professionals are open to transformation and interested in continuous learning.

While all indicators fell within the “agree” range, lower scores for items like commitment to explore AI ($M = 2.68$) suggest that passive acceptance may outpace active experimentation. Although auditors are generally supportive, translating that intention into real-world usage may require stronger motivation or structured organizational initiatives, such as mentorship programs, and performance-based incentives, and hands-on.

Table 3. Significant Differences in AI Acceptance and Behavioral Intention

Profile Variable	Test Statistic	p-value	Interpretation
Age	30.114–38.62	0.000	Significant Difference
Gender	20687.5–21141.5	>0.05	Not Significant
Position	45.991–54.368	0.000	Significant Difference
Experience	68.332–79.465	0.000	Significant Difference
Familiarity	386.648–388.158	0.000	Significant Difference
Personality	82.689–89.586	0.000	Significant Difference

Statistical tests revealed significant differences in AI acceptance and behavioral intention across several demographic and professional categories: age, job position, years of experience, familiarity with AI, and personality. The p-values for these variables were all below 0.05, confirming meaningful variations. For instance, younger auditors and those with higher AI familiarity exhibited stronger intentions and more favorable perceptions, aligning with prior findings that digital natives are more comfortable adopting new technologies.

In contrast, no significant differences were observed based on gender, indicating that male and female professionals share similar attitudes toward AI in auditing. This supports the idea that AI perception is more strongly influenced by exposure and context than by biological or social identity. These insights can guide targeted training efforts, particularly for older professionals or those in senior roles, who may benefit from customized capacity-building activities.

Table 4. Relationship Between AI Acceptance and Behavioral Intention

Acceptance Construct	Correlation Coefficient (r)	p-value	Interpretation
Performance Expectancy	0.930	0.000	Significant Relationship
Effort Expectancy	0.936	0.000	Significant Relationship
Social Influence	0.927	0.000	Significant Relationship
Facilitating Conditions	0.928	0.000	Significant Relationship

The correlation analysis demonstrated robust, statistically significant positive relationships between the four UTAUT constructs and behavioral intention, with correlation coefficients ranging from 0.927 to 0.936 ($p = 0.000$ for all). This confirms that increased acceptance in terms of perceived usefulness, ease of use, social support, and enabling conditions directly correlates with a stronger intention to use AI in internal audit tasks.

Among the constructs, Effort Expectancy showed the strongest correlation ($r = 0.936$), suggesting that making AI tools user-friendly and intuitive is critical to motivating actual use. Close behind were Performance Expectancy and Facilitating Conditions, emphasizing the importance of both practical benefits and available support structures. These findings reinforce the importance of holistic adoption strategies that enhance both personal and organizational readiness.

Table 5. Proposed Action Plan for Improving AI Adoption in Auditing

Key Result Area	Activity	Persons Involved	Desired Outcome
Performance Expectancy	Share success stories and present AI's audit benefits	Senior Auditors, IT Team, Dept. Heads	Improve perception of AI's value
Effort Expectancy	Provide intuitive tools and hands-on training	UX Designers, Training & IT Departments	Ease of use and increased confidence
Social Influence	Establish peer support groups and recognize AI advocates	HR, Senior Auditors, Management	Create a culture of collaborative AI acceptance
Facilitating Conditions	Provide hardware/software and gather employee feedback	IT, Procurement, HR	Strengthen organizational readiness and infrastructure
Behavioral Intention	Organize workshops and incentive programs	HR, Senior Management, IT	Boost motivation and actual use of AI tools

The proposed action plan was designed to align with the UTAUT model and directly address identified gaps in acceptance and behavioral intention. Each key result area was matched with actionable strategies, such as storytelling to enhance Performance Expectancy and peer-led training to strengthen Social Influence. Targeted workshops, intuitive interfaces, and IT support were emphasized as critical enablers for boosting familiarity and confidence in AI use.

Organizational stakeholders such as HR, department heads, and IT departments were assigned key roles in executing the plan, reflecting the need for cross-functional collaboration. The action plan's overall goal is to transition auditors from passive agreement to active participation, fostering a culture that not only welcomes but also sustains AI integration in internal audit functions.

4. DISCUSSION

The study revealed a generally favorable acceptance of AI in internal auditing across all four UTAUT constructs. Respondents agreed that AI can enhance audit effectiveness, though Performance Expectancy scored slightly lower, indicating cautious optimism. This aligns with Abdullah and Almaqtari (2024), who highlighted AI's transformative role in audit quality and efficiency.

Effort Expectancy received the highest mean score, suggesting that respondents find AI tools easy to use. However, slightly lower ratings on training material clarity point to a need for better-designed learning resources. This supports Shahzadi et al. (2024), who stressed the role of practical, clear training in boosting adoption.

Social Influence and Facilitating Conditions were also positively rated. Respondents acknowledged client and organizational expectations, indicating external pressure supports AI use. Yet, the perceived limited role of professional institutions suggests an advocacy gap, as discussed by Fetais et al. (2022) and Daidj (2022).

Auditors expressed strong behavioral intention to adopt AI, especially in attending training and recommending tools. However, lower scores on exploring AI tools independently reflect a passive attitude. These findings echo Virmani et al. (2024), who noted that engagement depends on motivation and structured opportunities.

Significant differences in acceptance and intention were linked to age, position, experience, familiarity, and personality, with younger and more familiar users showing higher scores. These trends align with Fedorko et al. (2021) and Şen (2023), who emphasized the influence of digital fluency on tech adoption readiness.

Finally, all four acceptance constructs showed strong positive correlations with behavioral intention, validating the UTAUT model. As Attié and Meyer-Waarden (2022) noted, usefulness, ease of use, social encouragement, and support systems are key drivers of AI adoption. Addressing these areas can enhance implementation success in auditing.

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