Auditing Transformation: A Model of Artificial Intelligence Adoption

Joseph B. O'Donnell
Canisius University

Auditors using artificial intelligence (AI) offers opportunities for transforming audits, and drastically improving audit effectiveness and efficiency. Generative AI, augmented AI, and AI performing an entire audit offer possibilities for enormous cost savings and the potential to dramatically improve audit quality. Obstacles to audit adoption include AI processing opaqueness, shortage of auditors with AI knowledge, a dearth of AI audit standards, and significant AI implementation costs. This paper develops a theoretical auditor AI adoption model utilizing innovation diffusion theory (IDT) and the Technology Acceptance Model (TAM). The paper provides suggestions for facilitating auditors' adoption of AI.

Keywords: artificial intelligence, auditing, accounting, Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), generative AI, auditor AI adoption

INTRODUCTION

Artificial intelligence (AI) offers the opportunity to dramatically improve the effectiveness and efficiency of the auditing process. The combination of vast amounts of data, advances in data analytics tools and AI provide the potential to transform the auditing process. Increasingly businesses are making data-driven decisions and auditors are looking to keep pace with the data-driven audit (AICPA & CPA Canada, 2020). AI enabled scans of client data sets provide the capability to effectively test 100% of the transactions and identify trends that might go undetected by humans. Employing AI across audit phases offers opportunities to perform routine and repetitive audit tasks more efficiently. In addition, AI could assist in audit risk assessment in the audit planning process and in identifying fraudulent transactions (Ho, 2023). Countering substantial AI auditing benefits are significant hurdles to adoption, such as AI processing's lack of transparency, AI implementation costs, shortage of auditors with AI knowledge, and an absence of AI audit standards.

This paper develops a theoretical model of the antecedent factors that affect the adoption of AI for auditing utilizing the diffusion of innovation theory and the Technology Acceptance Model (TAM). Modern technologies provide robust testing capabilities and efficiencies, but some auditors have been reluctant to use these technologies. The success of AI for auditing depends on the audit profession's adoption of this transformative innovation. Auditors from large firms have adopted AI and automation such as machine learning and robotic process automation (Bakarich & O'Brien, 2021). However, these adoptions do not come close to meeting the prediction of AI regularly performing entire audits by the year 2025 (World Economic Forum, 2015).

Prior research addresses auditors' use of AI in machine learning, data mining, block chain, decision support and expert systems (Handoko, 2021; Zemánková, 2019; Ukpong et al., 2019; Hasan, 2022).

However, there is a lack of prior research on auditor generative AI adoption and auditors employing AI to perform an entire audit. This paper helps address this research gap by creating a theoretical adoption model that investigates a broader range of AI activities, including generative AI and autonomous AI, where AI performs audits independently.

This paper develops a theoretical model of the antecedent factors that affect the adoption of AI for auditing utilizing diffusion of innovation theory and the Technology Acceptance Model (TAM). Diffusion of innovations is an extensive area of research that involves adopting new ideas, inventions, and new ways of doing things (Rogers, 2003). TAM is a widely used theory that addresses perceived ease of use and perceived usefulness in adoption of information technology (Davis, 1989). This paper's model addresses the influence of the characteristics of AI for auditing and attributes of auditors on the adoption of this innovation. The theoretical model provides a further understanding of technological adoption of auditing innovations. Auditors could benefit from the paper by using the theoretical model to develop strategies to promote the greater use of AI for auditing.

BACKGROUND INFORMATION

CPA Canada and American Institute of Certified Public Accountants (AICPA) (2020, p. 2) define Artificial intelligence (AI) as "the science of teaching programs and machines to complete tasks that normally require human intelligence." AI spans three different capability levels: assisted intelligence, augmented intelligence, and autonomous intelligence (Rao, 2017). Assisted intelligence encompasses simple tasks performed entirely by AI. "Assisted intelligence involves clearly defined, rules-based, repeatable tasks" (Rao, 2017). This capability level works only with clearly defined inputs and outputs. Examples include low level personal assistants, monitoring systems, and speech recognition software.

Augmented intelligence combines the performances of people and machines. Unlike assisted intelligence, automated intelligence alters the nature of the task (Rao, 2017). It extends human thinking abilities through collaborative human-machine decision-making (Rao, 2017). An example of augmented intelligence is an auditor using machine learning algorithms to analyze revenue trends that may have gone undetected by individuals. The auditor then evaluates and acts on the previously undetected trend. Augmented intelligence may impact senior decision-makers, in providing new alternatives that do not match their prior experiences and intuitions (Rao, 2017).

Autonomous intelligence occurs when AI performs complex tasks entirely on its own. Autonomous intelligence systems "make decisions without direct human involvement or oversight" (Rao, 2017). Examples of this capability level are automated trading in stock markets, self-driving cars and AI performing an entire audit on its own.

These three AI capability levels span distinct levels of change in AI for auditing. Assisted intelligence involves low levels of change, automating current processes using AI. Assisted intelligence is a good match for replacing routine and mundane audit tasks (Rao, 2017). Augmented intelligence encompasses moderate levels of change through process changes and introducing perspectives. Auditors overseeing the process and evaluating the outputs of augmented intelligence lessen the risk of this modern auditing approach. Autonomous intelligence involves a massive level of change in processes and decision-making. It may radically reengineer audit processes and result in AI performing an entire audit.

Another way to categorize AI is by type of activity. A common categorization is generative and non-generative AI. Generative AI creates patterns and generates content such as text, images, video, programming code and music (Marr, 2023). "Generative AI can improve a highly skilled worker's performance by as much as 40% compared with workers who don't use it" (Somers, 2023). Generative AI for auditing offers opportunities such as creating schedules, writing memos, creating audit plans, and writing audit opinions. Generative AI affects audits by replacing or augmenting repetitive and mundane tasks. Non-generative AI does not generate content and instead performs computations based on inputs, such as pattern recognition. Non-generative AI examples include trend recognition, facial recognition, speech recognition, classifying images, translating languages, and making predictions. AI possesses the ability to improve analytic models through model feedback. Audit examples are use of machine learning and deep learning for analysis of financial trends and text mining to evaluate contract terms (Ho, 2023). The mix of AI tools in an audit may encompass a holistic use of generative and nongenerative tools. For example, a holistic approach occurs when non-generative intelligence analyzes transaction trends and then generative AI creates a memo summarizing the trend analysis.

AI offers valuable potential uses in the audit process. Importantly, AI enables testing 100% of transactions rather than sampling (Ho, 2023). Evaluating all transactions through machine learning improves audit evidence used to support auditor decision-making and opinions. Automating routine and repetitive audit tasks, such as documenting interview notes and setting up audit schedules, with generative AI improves audit efficiency. Use of machine learning for contract review for key terms increases audit effectiveness by eliminating human error while more efficiently performing this audit task (Ho, 2023).

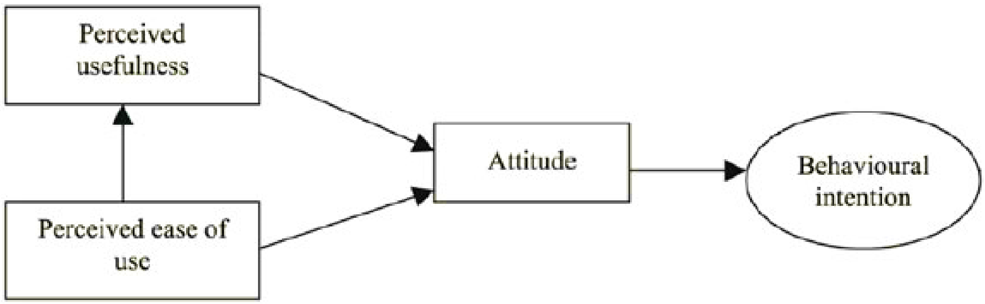
AI offers opportunities for improvement in auditors' risk assessment by performing frequent analysis of company internal and external data. Risk assessment is a critical part of the audit process as it is the foundation of an auditor's game plan for performing the audit. AI facilitates ongoing risk assessment of relevant and significant current events (Ho, 2023). AI evaluates the risk impact of transactions as they occur so that, where merited, risk levels are adjusted. In contrast, traditional risk assessments occur at the beginning (planning) stage of the audit and then updated periodically as auditors become aware of significant transactions affecting the risk assessment.

While AI use has valuable benefits, auditors need to consider significant potential constraints. First, new auditing skills are required as auditors need to be familiar with AI techniques and possess a degree of information technology (IT) knowledge (Dennis, 2024; Gambhir & Bhattacharjee, 2022; Mpofu, 2023). More university programs that combine accounting and AI curriculum are needed to provide this knowledge and these skills (Holmes, 2022). Second, the lack of transparency in AI processing creates a situation where auditors encounter difficulty in understanding and explaining the processes, and sources of data used to generate AI results. This lack of transparency also leads to difficulty verifying the data's accuracy and evaluating any potential intellectual property issues (Appel, 2023). Third, a shortage of AI auditing standards results in auditor uncertainty on the appropriate use of AI which could impact audit quality and expose auditors to legal liability should a lawsuit arise (Omoteso, 2012). AI auditing frameworks exist (for example Institute of Internal Auditors, 2018). Still, there is a dearth of detailed audit standards on the effectiveness of using AI and auditor knowledge requirements for using AI (Tang & Khondkar, 2017). Lastly, additional investments in AI technology, providing auditor training in AI, and substantial AI implementation costs may dissuade auditors from adopting AI (Dennis, 2024).

LITERATURE REVIEW

Considering the vast auditing AI benefits and AI's significant hurdles to adoption, it is useful to analyze auditors' adoption of AI through the lens of established diffusion and technology acceptance theories. This research paper focuses on two major streams of research: factors affecting the diffusion of innovations (Rogers, 2003) and the technology acceptance model (TAM) (Davis, 1989). This paper proposes a Theory of Adoption of Artificial Intelligence in Auditing (TAAIA) model based on integrating innovation diffusion theory (IDT) from a sociological perspective of innovation (Rogers, 2003) with the technology adoption/user acceptance theories as embodied in the Technology Acceptance Model (TAM) (Davis, 1989). TAM includes the effects of perceived usefulness and perceived ease of use on attitude towards using technology, affecting the intention to use technology (see Figure 1). Five factors in IDT represent antecedents of the two essential constructs in TAM. Prior researchers integrate these theories to explain innovation adoption and use (for example: Jeyaraj et al., 2006; King & He 2006; Lee et al., 2011; Schepers & Wetzels 2007; O'Donnell & Sauer, 2018, O'Donnell, 2006). This paper uses this literature stream in formulating the TAAIA model.

FIGURE 1
TECHNOLOGY ACCEPTANCE MODEL (TAM)



Davis, 1989

One theory employed in developing TAAIA stems from Rogers' (2003; 1983) work on diffusion of innovations in providing five antecedents operationalized as adopter's perceptions of the innovation. The first antecedent, *Relative Advantage*, "is the perception that an innovation will be superior to existing practices" (Rogers, 2003, p 15; Moore & Benbasat, 1991). Second, *Compatibility* is "the degree to which an innovation is compatible with existing values, past experiences and needs of the adopters" (Rogers, 2003, p. 15). Third, *Complexity* is "the degree to which an innovation is difficult to use and understand" (Rogers, 2003, p. 16). Fourth, Trialability "is the degree to which an innovation may be experimented with on a limited basis" (Rogers, 2003, p. 16). Finally, *Observability* is "the degree to which the results of an innovation are visible to others" (Rogers, 2003, p.16).

Two additional factors, *Firm Size* and *Trus*t, are added to Rogers' five antecedents in the TAAIA. Larger organizations generally possess more resources to adopt new technology (Grover & Teng, 1992). *Firm Size* is positively associated with AI adoption for businesses across different industries (Dinlersoz et al., 2020). Bakarich & O'Brien (2021) found that audit firm size was a significant factor in adopting machine learning and robotic process automation technologies. The Big 4 accounting firms invest more in these AI technologies and in training employees to use these technologies (Bakarich & O'Brien, 2021). Thus, it is reasonable that larger accounting firms are more likely to employ AI for audit purposes than smaller firms.

The perception of *Trust* between partners correlates positively with increases in the diverse use of inter-organizational systems (Hart & Saunders, 1998). Auditor's *Trust* in the accuracy of the clients' data is a key factor in the adoption process. AI requires accurate and reliable data (Institute of Internal Auditors, 2018). In addition, auditors test controls surrounding the generation and maintenance of financial data to gain confidence in the accuracy of this data. Thus, the greater the auditors' *Trust* in clients' data, the more likely auditors will use AI.

The second theory employed in developing our TAAIA model is the Technology Acceptance Model (TAM) (Davis 1989), which is derived from the Theory of Planned Behavior (Fishbein & Ajzen, 1985). TAM has extensively been used to explain technology adoption by individuals and organizations. The extensive literature arising from TAM has been analyzed in a variety of ways (Wu & Lederer, 2009; Yousafzai et al., 2007a; Yousafzai et al., 2007b; Ma & Liu, 2004; King & He, 2006; Schepers & Wetzels, 2007). A limitation of TAM is that the model does not consider the effect of external factors, such as the social network, on technology adoption (Bhattacherjee & Sanford, 2006). For instance, the influence of media and thought leaders may affect an individual's choice of adoption (Bhattacherjee & Sanford, 2006). IDT encompasses aspects of social networks, such as earlier adopters telling later adopters about the benefits of an innovation (Rogers, 2003). Integrating TAM and IDT lessens TAM's shortcomings by including external factors.

Subsequent research investigated variations of TAM utilizing alternative antecedents of TAM variables, including the User Acceptance of Information Technology (UTAUT) model (Venkatesh et al., 2003), the Lifestyle Technology Acceptance Model (LTAM) (Altemeyer, 2014) and similar enhancements (Benbasat & Barki 2007). Jeyaraj, Rottman, and Lacity (2006) identify eight related theories and associated models, some of which are variations of TAM, namely, TAM-II and TUAUT (Venkatesh et al., 2003). The author chose TAM over the TAM variation models as TAM's lean model integrates well with Roger's IDT approach.

While IDT and TAM have been used extensively for technology adoption research, there is much less research on adopting technology for AI audit purposes. The prior adoption research relates primarily to nongenerative AI uses such as machine learning (for example: Handoko, 2021 and Handoko et al., 2024). Handoko (2021) analyzed machine learning in the context of technology, organization, and environment factors. Handoko et al. (2024) applied a Technology Readiness Acceptance Model (TRAM) to auditors' adoption of machine learning. TRAM integrates TAM with a Technology Readiness Index (TRI) that emphasizes an individual's readiness to experience and use new technologies (Handoko et al., 2024). They found that innovation is an antecedent to perceived usefulness and ease of use while optimism is an antecedent to perceived ease of use.

AI in auditing adoption research has focused on nongenerative AI such as robotics, machine learning, neural networks, document review, speech recognition, and decision support systems (Handoko, 2021; Zemánková, 2019; Ukpong et al., 2019; Hasan, 2022). There is a shortage of generative AI and autonomous auditing with AI adoption research. This paper begins to fill this gap in the research community.

RESEARCH OBJECTIVES

- *What are the antecedents to AI adoption for the audit firm?*
- *Do the antecedents of AI auditing adoption differ from those of other information technology innovations?*

Given the AI benefits, potential limitations, and associated costs, this paper investigates the following question: what is the likelihood that auditors will adopt different levels of AI for auditing in the future? More specifically, what are the antecedents to AI for auditing adoption, and how can audit firm management use the antecedents to positively influence the pace of the adoption process? In addition, the paper looks at how these AI for auditing antecedents affect adoption relative to those of other information technology innovations?

APPLYING MODEL FACTORS TO AI

In developing an adoption model, it is useful to investigate the application of model factors to auditing with AI. As mentioned previously, the factors include five IDT elements (*Relative Advantage, Compatibility, Complexity, Trialability* and *Observability*) and *Firm Size* and *Trust*.

Relative Advantage involves the auditor perceiving that the use of AI is better than the current approach (Rogers, 2003). AI has the potential to significantly improve the efficiency of the audit by reducing the manual components of performing an audit. It enables the automation of repetitive and mundane tasks. AI could increase effectiveness by providing otherwise undetected insights, performing more extensive and frequent risk assessment, and testing the entire population of transactions. Fedyk et al. (2022) studied the thirty-six largest firms and found that investments in AI are associated with improvements in audit quality and reduces fees charged to clients. A main benefit of generative AI is cost savings by automating repetitive, mundane tasks and documentation of audit activities. This will reduce personnel costs and improve audit effectiveness as auditors will have more time to focus on more important tasks. The use of generative AI and AI for transaction testing provides opportunities for improvement over current approaches. However, while AI performing a fully automated audit offers significant cost savings, it is unclear whether the audit quality will be maintained or improved under this approach.

Compatibility involves AI's consistency with auditor needs, past experiences, and values (Rogers, 2003). Auditor *Compatibility* varies for generative AI, non-generative AI, and autonomous AI. Auditors are looking for opportunities to improve audit quality and increase efficiency. Using generative AI for mundane and repetitive tasks is consistent with that need. Mostly, this use of generative AI is consistent with past adoptions of technology (for example electronic worksheets) to gain efficiency and reduce errors on less important tasks. Generative AI varies from past experiences and values when used to perform more important tasks such as creating a research memo on an important audit issue. An auditor for instance, might use AI as the starting point for a memo and then make changes to enhance this memo. However, what if the auditor reviews the memo but sees no need to make changes. In this case, AI is minimizing the importance of the auditor in the audit process, which is inconsistent with auditor values and past experiences. AI autonomously performing the entire audit would be a drastic change as AI would make decisions rather than the auditor. Therefore, AI performing the entire audit is incompatible with auditors' past experiences. Professional organizations issuing AI audit standards could reduce AI compatibility concerns by guiding appropriate audit use of AI.

Complexity involves auditors' perception of the involvedness of using AI. As AI *Complexity* increases, the likelihood of adopting an innovation decrease (Rogers, 2003). In general, AI is not complicated to use. For instance, generative AI allows users to submit topics and commands in plain English. Many AI analytic tools provide user friendly interfaces. However, the algorithms underlying AI processing may be opaque and can be considered a "black box" where auditors encounter difficulty in understanding and explaining the process used to generate AI results (Center of Audit Quality, 2024). This lack of AI transparency restricts auditors' ability to interpret the context of AI results. Furthermore, it hampers auditors in weighing the impact of AI results on audit decisions, determining appropriate auditor follow-up, and concluding on AI results' effect in supporting the audit opinion.

Auditors face challenges in determining the sources of created content for generative AI. One concern is that generative AI's use of sources could be violating intellectual property laws (Appel, 2023). For nongenerative AI, opaqueness of AI processing generates difficulties in understanding underlying algorithms and in determining which data are used for the analyses. This challenges auditors in gauging AI's effectiveness in performing audit tasks. The AI opaqueness would certainly create challenges for the auditor should AI be used to perform the entire audit. Explainable AI is a set of processes that explain an AI model. Explainable AI increases AI transparency (Saeed & Omlin, 2023) and expanded use of this technology reduces AI *Complexity*.

Trialability involves the ease of experimenting with AI. The easier one can experiment with AI the more likely AI will be adopted (Rogers, 2003). *Trialability* differs with generative and nongenerative AI. Public generative AI is readily available, easy to try out and free. However, privacy concerns abound with publicly available generative AI (Wu et al., 2024). Confidential information should not be used with public generative AI as chat information may be used to train AI models.

Consequently, audit firms tend to use private generative AI which may be expensive and, thus, more difficult for experimentation. Availability of firm resources to purchase and support private AI reduces the *Trialability* of generative AI. Regarding non-generative AI, such as machine learning, organizations require the necessary resources to develop in-house or purchase these tools. Thus, the *Trialability* of AI is limited by availability of firm resources.

Observability of AI involves the degree to which AI results are viewable to others. The more observable the AI results the more likely others will use AI (Rogers, 2003). *The observability* of AI for auditing is mixed. On one hand, accounting professional organizations are encouraging the use of AI tools and, describing examples and benefits of using the AI tools (AICPA & CPA Canada, 2020). Also, auditors of large companies see benefits of AI used at those companies (Bakarich & O'Brien, 2021). On the other hand, detailed AI use in particular audits and the specific results of AI use are confidential and not publicly shared.

Firm Size affects AI adoption as larger accounting firms invest more in AI and are more likely to adopt AI for auditing (Bakarich & O'Brien, 2021). In addition, larger accounting firms tend to audit larger companies who are more likely to use AI (Bakarich & O'Brien, 2021). Auditors at larger accounting firms are more likely to possess financial resources needed for AI implementation and their audit professionals tend to better understand AI benefits based on their client experiences than auditors at smaller firms.

Trust in the accuracy of client data is an important antecedent to auditor AI adoption. AI depends on accurate and reliable data for effective analysis and generation of information (Friend, 2023). Auditors gain confidence in financial data by performing tests of control surrounding the generation, maintenance and security surrounding the data. Auditors also may benefit from trusting nonfinancial client data which provides additional information on the client's financial performance, business opportunities and risks.

PROPOSITIONS

The following propositions represent the foundation for a theoretical model of auditors' adoption of AI.

P1: *Relative Advantage is an antecedent of Perceived Usefulness. Auditors will realize the ways in which AI for auditing offers a significant improvement over their previous practices and hence choose to adopt it to take advantage of this Perceived Usefulness. Proposition supported by prior technology adoption research by Al-Rahmi et al. (2019) on adoption of electronic learning systems.*

P2: *Firm Size is an antecedent of Perceived Usefulness. Larger firms are more likely to possess the financial resources to support hiring AI expertise, AI training of employees and the technological infrastructure for AI processing. Big 4 accounting firms are more likely to utilize AI than smaller firms and their auditors are more receptive to future changes caused by AI use (Bakarich & O'Brien, 2021). This proposition is consistent with prior large investment (ERP) software adoption research (Faith-Michael et al., 2008).*

P3A: *Complexity is an antecedent of, but negatively associated with, Perceived Usefulness. The lack of transparency of the AI algorithms reduces the auditors' understanding of the tasks performed by AI and reduces auditors' ability to rely on AI results for audit decision-making. This Complexity and Perceived Usefulness relationship is consistent with previous technology adoption research (Al-Rahmi et al., 2019).*

P3B: *Complexity is an antecedent of, but will negatively affect, Perceived Ease of Use. AI's algorithm opaqueness creates challenges for auditors in explaining and defending AI results. The relationship of these factors is consistent with Al-Rahmi et al. (2019).*

P4A: *Trust is an antecedent of Perceived Usefulness. The greater the auditors' Trust in the quality and security of the clients' data the greater the perception that auditing with AI is useful for analyzing the data more effectively. This proposition is consistent with the findings of prior research that Trust influences Perceived Usefulness (Gefen et al., 2003; Lee, 2009; Ortega Egea & Román González, 2011; Pavlou, 2003; Tung et al., 2008; Wu & Chen, 2005).*

P4B: *Trust is an antecedent of Perceived Ease of Use as the auditors' Trust in the quality of the clients' data will increase the perception that auditing with AI is easier to use. This is consistent with prior research that Trust influences Perceived Ease of Use (Ortega Egea et al., 2011; Pavlou, 2003) but not consistent with other researchers that determined that Perceived Ease of Use influences Trust (Gefen et al., 2003; Tung et al., 2008; Lee, 2009). Importance of the Trust in quality data inputs to the AI process supports Trust being an antecedent of Perceived Ease of Use.*

P5: *Observability is an antecedent of Perceived Usefulness. This proposition is supported by the positive effect of result demonstrability on adoption as shown in the Mun et al. (2007) study.*

P6A: *Compatibility of auditing with AI is an antecedent of Perceived Usefulness. Increases in Compatibility of auditing with AI with existing auditor values, past auditor experiences and auditor needs most likely lead auditors to positively view AI's benefits. Proposition is consistent with Al-Rahmi et al. (2019) findings.*

P6B: *Compatibility of auditing with AI is an antecedent of Perceived Ease of Use. This proposed relationship is based on greater compatibility resulting in a smaller learning curve for auditors in using AI. Proposition is consistent with Al-Rahmi et al. (2019) research study.*

P7: *Trialability is an antecedent of Perceived Usefulness. The more the auditor can experience auditing with AI, by using it, the greater the Perceived Usefulness of auditing with AI. Proposition is consistent with Al-Rahmi et al. (2019) findings.*

P8A: *Perceived Ease of Use is an antecedent of Perceived Usefulness. Supported by technology acceptance model (Davis, 1989) and machine learning research (Handoko et al., 2024)*

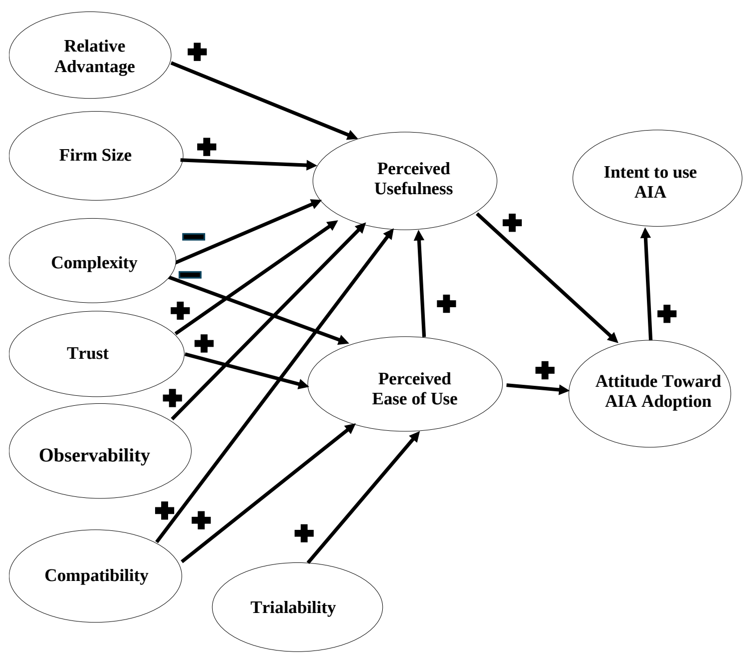
P8B: *Perceived Ease of Use is an antecedent of Attitude Toward AIA (Auditing with AI) Adoption. Proposition consistent with technology acceptance model (Davis, 1989).*

P9: *Perceived Usefulness is an antecedent of Attitude Toward AIA Adoption. Proposition consistent with technology acceptance model (Davis, 1989).*

P10: *Attitude Toward AIA Adoption is an antecedent of Intent to use AIA. Proposition consistent with technology acceptance model (Davis, 1989).*

The resulting TAAIA model, see Figure 2, incorporates these propositions by integrating IDT and TAM theories.

FIGURE 2
THEORY OF ADOPTION OF ARTIFICIAL INTELLIGENCE IN AUDITING (TAAIA) MODEL



DISCUSSION

This paper describes a theoretical model of Theory of Adoption of Artificial Intelligence in Auditing (TAAIA) formulated by integrating the underlying theories that form the foundation of the diffusion of innovation (IDT) theory and the technology acceptance model (TAM). The TAAIA model provides a rich framework ready for empirical validation. The theoretical model is developed based on published research findings on diffusion and adoption of previous innovations and technologies. An empirical study of auditors is needed to confirm this integrated model. A recommended first step in understanding and evaluating the validity of this paper's model would be to use an exploratory case study of an accounting firm and its use of AI for auditing. Such a study would assist in developing a better understanding of the direction and strength of the factor relationships in the model. This will provide further fine-tuning of the factors influencing the adoption, and the extent of adoption, of TAAIA. This will allow researchers to further refine the TAAIA model before empirically testing it through survey-based research of AI adoption at the firm level. Finally, a study of the differences and relationships between the adoption by an audit firm and adoption by an individual auditor within a firm would enhance researchers' understanding of the organizational influences on the antecedents leading to AI for auditing adoption.

For audit professionals, two major hurdles to AI adoption are the absence of auditing standards and the lack of transparency of AI algorithms and data sources. Professional audit standards could facilitate the adoption of AI by providing guidance on the use of generative AI and autonomous intelligence, where AI performs an entire audit. Auditing standards should address when it is appropriate to use generative AI and disclosure requirements when using this form of AI. Auditing guidance is critical to outline situations where AI performs an entire audit. Audit standards provide guidance on the responsibilities of external auditors in relying on the audits performed by internal auditors (AICPA, 2021) and auditors would benefit from similar guidance when relying on audits performed by AI. In addition, auditing standards could help auditors understand the acceptable level of AI use in various audit situations.

Improving transparency of AI algorithms and data sources through tools, such as Explainable AI (Saeed & Omlin, 2023), could expand auditors' use of AI. The "black box" of AI processing makes it challenging for auditors to understand and defend AI results. Transparency of AI algorithms is needed for auditors to comprehend the logic and procedures creating the AI results. Transparency of data sources would allow auditors to evaluate appropriateness of the data used by AI.

CONCLUSION

This paper develops a theoretical model to analyze technology adoption antecedents of using Theory of Adoption of Artificial Intelligence in Auditing (TAAIA). The TIAAIA model integrates theoretical foundations of diffusion of innovations and acceptance of information technology and incorporates TAAIA characteristics. The paper provides a framework for the auditing profession's understanding of the adoption of TAAIA and a starting point for empirical research in this area. It could give the audit firm a better understanding of the resistance points and reasons for auditors accepting and adopting AI for auditing.

REFERENCES

AICPA. (2021). Using the Working of Internal Auditors. *Statement on Accounting Standards, AU-C Section*, *610*, 941–959.

AICPA & CPA Canada. (2020). The data-driven audit: How automation and AI are changing the audit and the role of the auditor. *Chartered Professional Accountants of Canada*, 1–34.

Al-Ateeq, B., Sawan, N., Al-Hajaya, K., Altarawneh, M., & Al-Makhadmeh, A. (2022). Big data analytics in auditing and the consequences for audit quality: A study using the technology acceptance model (TAM). *Corporate Governance and Organizational Behavior Review*, *6*(1), 64–78.

Al-Rahmi, W.M., Yahaya, N., Aldraiweesh, A.A., Alamri, M.M., Aljarboa, N.A., Alturki, U., & Aljeraiwi, A.A. (2019). Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on students' intention to use E-learning systems. *Ieee Access*, (*7*), 26797–26809.

Altemeyer, B. (2014). *The importance of trust and cognitive ability measures in hedonic and utilitarian technology acceptance models: The development of the LTAM* (Doctoral dissertation, University of Westminster).

Appel, G., Neelbauer, J., & Schweidel, D.A. (2023). Generative AI has an intellectual property problem. *Harvard Business Review*, *7*.

Bakarich, K.M., & O'Brien, P.E. (2021). The robots are coming… but aren't here yet: The use of artificial intelligence technologies in the public accounting profession. *Journal of Emerging Technologies in Accounting*, *18*(1), 27–43.

Bhattacherjee, A., & Sanford, C. (2006) Influence processes for information technology acceptance: An elaboration likelihood model. *MIS Quarterly*, *30*(4), 805–825.

Center of Audit Quality. (2024). *Auditing in the age of generative AI*. Retrieved from https://www.thecaq.org/auditing-in-the-age-of-generative-ai

Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 425–478.

Dennis, A. (2024). What AI can do for auditors. *Journal of Accountancy*, *235*(2), 1–7. American Institute of Certified Public Accountants.

Dinlersoz, E., Goldschlag, N., Zolas, N., Beede, D.N., Foster, L.S., Kroff, Z., . . . Buffington, C. (2020). *Advanced technologies adoption and use by U.S. Firms: Evidence from the annual business survey*. NBER Working Paper Series. https://doi.org/10.3386/w28290

Faith-Michael, U., Abiola, R., & Nyangeresi, R. (2008). Influence of product and organizational constructs on ERP acquisition using an extended technology acceptance model. *International Journal of Enterprise Information Systems*, *4*(2), 67–83. https://doi.org/10.4018/jeis.2008040105

Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process? *Review of Accounting Studies*, *27*(3), 938–985. https://doi.org/10.1007/s11142-022-09697-x

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behaviour: An introduction to theory and research.* Reading, MA: Addison-Wesley.

Friend, D. (2023, August 10) AI is only as good as the data that trains it. *Forbes.* Retrieved from https://www.forbes.com/councils/forbestechcouncil/2023/08/10/ai-is-only-as-good-as-the-data-that-trains-it/

Golda, A., Mekonen, K., Pandey, A., Singh, A., Hassija, V., Chamola, V., & Sikdar, B. (2024). *Privacy and Security Concerns in Generative AI: A Comprehensive Survey.* IEEE Access.

Gambhir, B., & Bhattacharjee, A. (2022). Embracing the role of artificial intelligence in accounting and finance: Contemplating the changing skillset expectations. *Development and Learning in Organizations*, *36*(1), 17–20. Retrieved from https://doi.org/10.1108/DLO-01-2021-0016

Gefen, D., Karahanna, E., & Straub, D.W. (2003) Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, *27*(1), 51–90.

Grover, V., & Teng, J.T.C. (1992). An examination of DBMS adoption and success in American organizations. *Information & Management*, *23*(5), 239–248.

Handoko, B.L. (2021). How audit firm size moderate effect of TOE context toward auditor adoption of machine learning. *Journal of Theoretical and Applied Information Technology*, *99*(24), 5972–5980.

Handoko, B.L., Indrawati, D.S., & Zulkarnaen, S.R.P. (2024). Embracing AI in auditing: An examination of auditor readiness through the TRAM framework. *International Journal of Computational Methods and Experimental Measurements*, *12*(1), 53–60. https://doi.org/10.18280/ijcmem.120106

Hasan, A.R. (2022). Artificial intelligence (AI) in accounting & auditing: A literature review. *Open Journal of Business and Management*, *10*(1), 440–465. https://doi.org/10.4236/ojbm.2022.101026

Ho, C. (2023, November 3). *Can artificial intelligence transform auditing and our fear of that transformation?* Speech at Rutgers Business School 58th World Continuous Auditing & Reporting Symposium. Retrieved from https://pcaobus.org/news-events/speeches/speech-detail/can-artificial-intelligence-transform-auditing-and-our-fear-of-that-transformation

Holmes, A.F., & Douglass, A. (2022). Artificial intelligence: Reshaping the accounting profession and the disruption to accounting education. *Journal of Emerging Technologies in Accounting*, *19*(1), 53–68. https://doi.org/10.2308/JETA-2020-054

Ionescu, L. (2022). Machine learning-based decision-making systems, cloud computing and blockchain technologies, and big data analytics algorithms in accounting and auditing. *Economics, Management, and Financial Markets*, *17*(4), 9–26. https://doi.org/10.22381/emfm17420221
Institute of Internal Auditors. (2018). *Global perspectives and insights: The IIA's artificial intelligence auditing framework, practical applications, part B*. Retrieved from https://www.theiia.org/
Jeyaraj, A., Rottman, J.W., & Lacity, M.C. (2006). A review of the predictors, linkages, and biases in IT innovation adoption research. *Journal of Information Technology*, *21*(1), 1–23.
King, W.R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information and Management*, *43*(6), 740–755.
KPMG. (2023). *KPMG U.S. survey: Executives expect generative AI to have enormous impact on business, but unprepared for immediate adoption.* Retrieved from https://kpmg.com/us/en/media/news/kpmg-generative-ai-2023.html.
Lee, M. (2009). Predicting and explaining the adoption of online trading: An empirical study in Taiwan. *Decision Support Systems*, *47*, 133–142.
Lee, Y.H., Hsieh, Y.C. & Hsu, C.N. (2011). Adding innovation diffusion theory to the technology acceptance model: Supporting employees' intentions to use e-learning systems. *Educational Technology and Society*, *14*(4), 124–137.
Ma, Q., & Liu, L. (2004). The technology acceptance model: A meta-analysis of empirical findings. *Journal of Organizational and End User Computing (JOEUC)*, *16*(1), 59–72.
Marr, B. (2023). The difference between generative AI and traditional AI: An easy explanation for anyone. *Forbes.* Retrieved from *https://www.forbes. com/sites/bernardmarr/2023/07/24/the-difference-between-generative-ai-and-traditional-ai-an-easy-explanation-for-anyone/*
Moore, G.C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3), 192–225.
Mun, Y.Y., Jackson, J.D., Park, J.S., & Probst, J.C. (2006). Understanding information technology acceptance by individual professionals: Toward an integrative view. *Information and Management*, *43*(3), 350–363.
Mpofu, F.Y. (2023). The application of artificial intelligence in external auditing and its implications on audit quality? A review of the ongoing debates. *International Journal of Research in Business and Social Science (2147- 4478)*, *12*(9), 496–512. https://doi.org/10.20525/ijrbs.v12i9.2737
O'Donnell, J.B. (2006). Innovations in audit technology: A model of continuous audit adoption. *Journal of Applied Business and Economics*, *6*(5), 11–20.
O'Donnell, J.B., & Sauer, P.L. (2018). A model of accountants' adoption of big data analytics in auditing. *The BRC Academy Journal of Business*, *8*(1), 23–43.
Omoteso, K. (2012). The application of artificial intelligence in auditing: Looking back to the future. *Expert Systems with Applications*, *39*, 8490–8495. https://doi.org/10.1016/j.eswa.2012.01.098
Ortega Egea, J.M., & Román González, M.V. (2011). Explaining physicians' acceptance of EHCR systems: An extension of TAM with trust and risk Factors. *Computers in Human Behavior*, *27*(1), 319–332.
Pavlou, P.A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 69–103.
Rao, A. (2017). A strategist's guide to artificial intelligence. *Strategy + Business*, *87*, 46–50. Retrieved from: https://www.strategy-business.com/article/A-Strategists-Guide-to-Artificial-Intelligence
Rogers, E.M. (2003). *Diffusion of Innovations* (5th ed.). New York: Free Press.
Saeed, W., & Omlin, C. (2023). Explainable AI (XAI): A systematic meta-survey of current challenges and future opportunities. *Knowledge-Based Systems*, *263*, 110273.
Schepers, J., & Wetzels, M. (2007). A Meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information and Management*, *44*(1), 90–103.
Somers, M. (2023). How generative AI can boost highly skilled workers' productivity. *Ideas That Matter.* MIT Sloan School of Management. Retrieved from https://mitsloan.mit.edu/ideas-made-to-matter/how-generative-ai-can-boost-highly-skilled-workers-productivity

Tang, J.J., & Karim, K.E. (2017). Big data in business analytics: Implications for the audit profession. *CPA Journal*, *87*(6).

Thomson Reuters Tax & Accounting. (2024, June 23). *How do different accounting firms use AI?* Retrieved from https://tax.thomsonreuters.com/blog/how-do-different-accounting-firms-use-ai/

Tung, F., Chang, S., & Chou, C. (2008). An extension of trust and TAM model with IDT in the adoption of the electronic logistics information system in HIS in the medical industry. *International Journal of Medical Informatics*, *77*, 324–335.

Ukpong, E.G., Udoh, I.I., & Essien, I.T. (2019). Artificial intelligence: Opportunities, issues and applications in banking, accounting, and auditing in Nigeria. *Asian Journal of Economics*, *Business and Accounting, 10*, 1–6. https://doi.org/10.9734/ajeba/2019/v10i130099

Venkatesh, V., Morris, M.G., Davis, G.B. & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view, *MIS Quarterly*, *27*(3), 425–478.

Wu, I., & Chen, J. (2005). An extension of trust and TAM model with TPB in the initial adoption of on-line tax: An empirical study. *International Journal of Human-Computer Studies*, *62*, 784–808.

Wu, X., Duan, R., & Ni, J. (2024). Unveiling security, privacy, and ethical concerns of ChatGPT. *Journal of Information and Intelligence*, *2*(2), 102–115.

Wu, J., & Lederer, A. (2009). A meta-analysis of the role of environment-based voluntariness in information technology acceptance. *MIS Quarterly*, *33*(2), 419–432.

World Economic Forum. (2015). *Deep shift technology tipping points and societal impact*. Retrieved from https://www.weforum.org/publications/deep-shift-technology-tipping-points-and-societal-impact/

Yoon, K., Hooqduin, L., & Zhang, L. (2015) Big data as complimentary evidence. *Accounting Horizons*, *29*(2), 431–438.

Yousafzai, S.Y., Foxall, G.R., & Pallister, J.G. (2007a). Technology Acceptance: A meta-analysis of the TAM: Part 1. *Journal of Modelling in Management*, *2*(3), 251–280.

Yousafzai, S.Y., Foxall, G.R., & Pallister, J.G. (2007b). Technology Acceptance: A meta-analysis of the TAM: Part 2. *Journal of Modelling in Management*, *2*(3), 281–304.

Zemánková, A. (2019). Artificial intelligence and blockchain in audit and accounting: Literature review. *WSEAS Transactions on Business and Economics*, *16*, 568–581. Retrieved from https://www.wseas.org/multimedia/journals/economics/2019/b245107-089.pdf