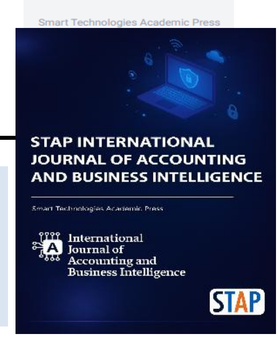


STAP
Smart Technologies Academic Press

**STAP International Journal of Accounting and Business Intelligence**
https://www.ijabi.thestap.com/

Check for updates

# The Moderating Role of Institutional Pressures: Adoption of Emerging Technologies in Audit Firms under a Regulated Environment

**Mahmoud Ali jaradat,**[1]

[1] *Banking and Finance Department, Al al-Bayt University, Jordan,* Mahmoud.Jaradat@aabu.edu.jo

**ARTICLE INFO**

**Article History**

**Received:** 02-02-2025
**Revised:** 05-03-2025
**Accepted:** 05-04-2025
**Published:** 21-05-2025

**Vol.2025, No.1**

**DOI:**

***Corresponding author. Email:***

Mahmoud.Jaradat@aabu.edu.jo



## ABSTRACT

This study examines the determinants of emerging technology adoption (e.g., AI, blockchain, RPA, data analytics) in audit firms operating within a regulated environment, drawing on the Technology-Organization-Environment (TOE) framework. It analyzes the direct effects of technological competence, organizational absorptive capacity, and institutional pressures, and investigates the moderating role of the environmental context on these relationships. A quantitative survey design was employed, collecting data from 114 audit professionals. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), with measurement models ensuring reliability and validity and a structural model testing the hypotheses. The results validate the TOE framework, showing that organizational context (absorptive capacity) is the strongest predictor of adoption ($\beta = 0.79$, $p < 0.001$) followed by technological context ($\beta = 0.67$, $p < 0.001$) and environmental pressures ($\beta = 0.34$, $p < 0.05$). Crucially, normative pressure was found to be a significant positive moderator, while coercive and mimetic pressures were not. The study confirms that successful adoption in auditing hinges not just on technology but primarily on organizational learning capabilities and is significantly influenced by professional and regulatory norms. It offers practical insights for firms to prioritize capability building and for regulators to shape effective normative guidance, contributing to theory by integrating institutional and absorptive capacity perspectives into the TOE framework.

**Keywords:** Emerging Technologies; Technology Adoption; TOE Framework; Institutional Theory; Absorptive Capacity; Auditing; PLS-SEM.

**How to cite the article**

## 1. Introduction

The accounting profession has traditionally focused on calculation, transaction recording techniques, and information generation (Henry & Hicks, 2015). With professional advancements, accounting is undergoing a technological transformation, and audit services are evolving accordingly.

Digital transformation is characterized by the use of digital technologies to transform business processes, identify new revenue opportunities, and enable or improve business models (Majchrzak et al., 2016). This transformation presents significant research opportunities in auditing, such as understanding the factors influencing audit firms' decisions to adopt new technologies, the evolving knowledge demands placed on auditors, and the impact of emerging technologies on audit procedures (Witte, 2020).

Among the emerging technologies most used by audit firms are big data, artificial intelligence (AI), robotics (RPA), cognitive automation, virtual assistants, intelligent automation, cloud computing, blockchain, drones, the Internet of Things (IoT), 3D printing, and computer vision (Montes & Goertzel, 2019). These technologies are employed to enhance processes and services.

Previous studies have explored the effects of emerging technologies on firms, such as the use of big data and AI in data analysis (Warren et al., 2015) and external reporting (Al-Htaybat & Von Alberti-Alhtaybat, 2017). Others have examined the impact of digital technology on audit firm performance or risk analysis (Cao et al., 2015), the influence of technology on audit judgment quality (Brown-Liburd & Vasarhelyi, 2015), and the adoption of digital transformation in internal auditing (Vasarhelyi et al., 2015). However, there remains a gap in understanding the factors influencing the adoption of emerging technologies such as AI, big data, RPA, cloud computing, blockchain, drones, IoT, and audit data analytics (ADA) in external auditing (Widuri et al., 2019; Handoko, 2021).

The TOE framework is widely applied in research on IT adoption at the firm level (Oliveira & Martins, 2011; Venkatesh & Bala, 2012). It posits that three contextual factors influence decisions to adopt emerging technologies: technological context, organizational context, and environmental context (Baker, 2012; Tornatzky & Fleischer, 1990).

Given conflicting results regarding the role of the environmental context and its potential moderating effects (Rosli et al., 2016; Oliveira et al., 2019), this study aims to analyze the moderating role of the environmental context in the relationship between technological and organizational contexts and the adoption of emerging technologies by audit firms in a regulated environment.

## 2. Theoretical Framework

The adoption of emerging technologies in auditing can be examined through the Technology–Organization–Environment (TOE) framework, which provides a holistic perspective on how firms embrace innovation. Originally developed by Tornatzky and Fleischer (1990) and widely applied in Information Systems research (Oliveira & Martins, 2011), the TOE framework emphasizes that technological, organizational, and environmental factors collectively shape the decision to adopt new technologies. In the auditing domain, this framework has been increasingly applied to explain the adoption of AI-driven analytics, blockchain-enabled assurance, and continuous auditing tools (Singh et al., 2023; Rahman & Alsmadi, 2022; Appelbaum & Nehmer, 2017; Salijeni et al., 2019).

### 2.1. Technological Context

The technological dimension refers to the internal technological infrastructure and perceived benefits of adopting innovation. Firms with advanced IT capabilities are more likely to experiment with and integrate disruptive technologies, such as Robotic Process Automation (RPA), Blockchain, and AI-enhanced Audit Data Analytics (ADA) (Zhu & Kraemer, 2005; Tsou & Hsu, 2015). Recent studies suggest that technological competence directly affects adoption intensity, as firms with robust data infrastructure can better leverage continuous auditing and augmented analytics (Vitali, 2024; ResearchGate, 2025; Low et al., 2011). Moreover, auditors' perceptions of technological usefulness and ease of use, as posited by the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), strongly moderate adoption behavior (Venkatesh et al., 2012; Ferreira & Reis, 2021; Chan & Chong, 2013).

### 2.2. Organizational Context

The organizational context includes leadership support, resources, culture, and absorptive capacity for innovation. Firms that encourage cross-functional collaboration and provide training for digital skills are more likely to adopt emerging technologies in auditing (Zahra & George, 2002). For example, WestRock's internal audit function leveraged generative AI by fostering a culture of experimentation and knowledge-sharing (Deloitte WSJ, 2024). Similarly, KPMG (2024) reports that Australian firms embracing AI-based tools benefit from stronger internal control systems and improved fraud detection. Absorptive capacity, as conceptualized by Flatten et al. (2011) and Cohen & Levinthal (1990), plays a central role in facilitating the acquisition, assimilation, transformation, and application of new knowledge. Recent empirical evidence suggests that higher levels of digital literacy among employees accelerate adoption and reduce resistance to change (Martins & Oliveira, 2023; Ali & Park, 2016; Youssef et al., 2015).

### 2.3. Environmental Context

The environmental dimension emphasizes external pressures, including coercive, normative, and mimetic influences (DiMaggio & Powell, 1983; Scott, 2003). In auditing, coercive pressures emerge from regulators mandating digital compliance, such as the PCAOB and IFAC's emphasis on technology-driven audit quality (Dedoulis, 2016; Barr-Pulliam et al., 2022). Normative pressures stem from client expectations and professional networks advocating the use of advanced audit technologies (Mckinley & Mone, 2003; Coraiola & Machado-da-Silva, 2008). Mimetic pressures occur when organizations imitate competitors or industry leaders who adopt innovations, creating legitimacy and signaling trustworthiness (Rahman & Alsmadi, 2022; Carpenter & Feroz, 2001; Villadsen et al., 2010). The increasing globalization of audit markets and international benchmarking have amplified these pressures, making them critical to adoption decisions (Liang et al., 2007; Teo et al., 2003).

### 2.4. Integration of TOE with Emerging Trends

Recent scholarship argues that TOE should be integrated with dynamic capabilities theory to better capture the agility required in fast-changing digital environments (Wamba et al., 2023). For instance, organizations that develop dynamic capabilities in sensing, seizing, and reconfiguring resources are better positioned to adapt AI and blockchain tools in auditing practices (Bradley et al., 2011; Cui & Jiang, 2012). This integrated lens highlights that while technological readiness and organizational support are necessary, firms must also remain flexible in responding to evolving regulatory and competitive environments (DePietro et al., 1990; Oliveira, 2017).

## 3. Hypothesis Development

Drawing on TOE, the study posits that:

• H1: Technological context positively influences the adoption of emerging technologies in auditing.

• H2: Environmental pressures (coercive, normative, and mimetic) positively influence adoption.

• H3: Organizational context (absorptive capacity and leadership support) has the strongest positive impact on adoption.

These hypotheses are tested using PLS-SEM, enabling the examination of direct and mediating effects within a complex multi-construct model (Hair et al., 2014; Henseler & Fassott, 2010).

## 4. Methodology

### 4.1. Research Design

This study adopts a quantitative research design, applying the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique to examine the relationships between technological, organizational, and environmental contexts and the adoption of emerging technologies in auditing. PLS-SEM is particularly appropriate when the objective is to predict key target constructs and when theoretical development is still emerging (Hair et al., 2021). Unlike covariance-based SEM, PLS-SEM does not require data normality and is suitable for small to medium-sized samples, making it widely used in accounting and information systems research (Hair et al., 2014).

### 4.2. Data Collection and Sample

Data were collected through a structured questionnaire distributed to auditors, managers, and IT professionals in auditing firms and corporate internal audit departments. The survey included items adapted from validated measurement scales in prior studies:

• Technological Context (CT): Adapted from Chan & Chong (2013), focusing on IT infrastructure readiness and familiarity with emerging technologies.

• Organizational Context (CO): Adapted from Flatten et al. (2011), measuring absorptive capacity through acquisition, assimilation, transformation, and application of knowledge.

• Environmental Context (CA): Adapted from Liang et al. (2007), capturing coercive, normative, and mimetic pressures.

• Adoption of Emerging Technologies (ATE): Adapted from Venkatesh & Bala (2012), measuring adoption of tools such as RPA, Blockchain, and Audit Data Analytics (ADA).

Responses were measured using a seven-point Likert scale ranging from 1 (“strongly disagree”) to 7 (“strongly agree”). The Likert scale provides granularity in capturing perceptions and attitudes, and has been widely employed in information systems adoption studies (Hair et al., 2021; Martins & Oliveira, 2023).

**4.3. Reliability and Validity**

The measurement model was assessed through Cronbach’s Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) to ensure internal consistency and convergent validity (Fornell & Larcker, 1981). Discriminant validity was tested using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio, as recommended by Henseler et al. (2015). Threshold values of Cronbach’s Alpha > 0.70, CR > 0.70, and AVE > 0.50 were considered acceptable for reliability and validity.

**4.4. Structural Model Assessment**

The structural model was evaluated using path coefficients, t-statistics, p-values, and $R^2$ values to assess explanatory power. Effect sizes ($f^2$) and predictive relevance ($Q^2$) were also reported. Bootstrapping with 5,000 resamples was performed to test the significance of hypothesized relationships, a method grounded in the work of Kenny & Judd (1984) and later advanced for PLS-SEM (Henseler & Fassott, 2010). The use of bootstrapping in PLS-SEM is recommended for robust hypothesis testing in auditing and information systems research (See table 1 and figure 1 ) (Sarstedt et al., 2022; Hair et al., 2014).

Tables on measurement items, reliability/validity statistics (See table 2), and PLS-SEM (See table 3) results are included. The following figure illustrates the theoretical research model based on the TOE framework.

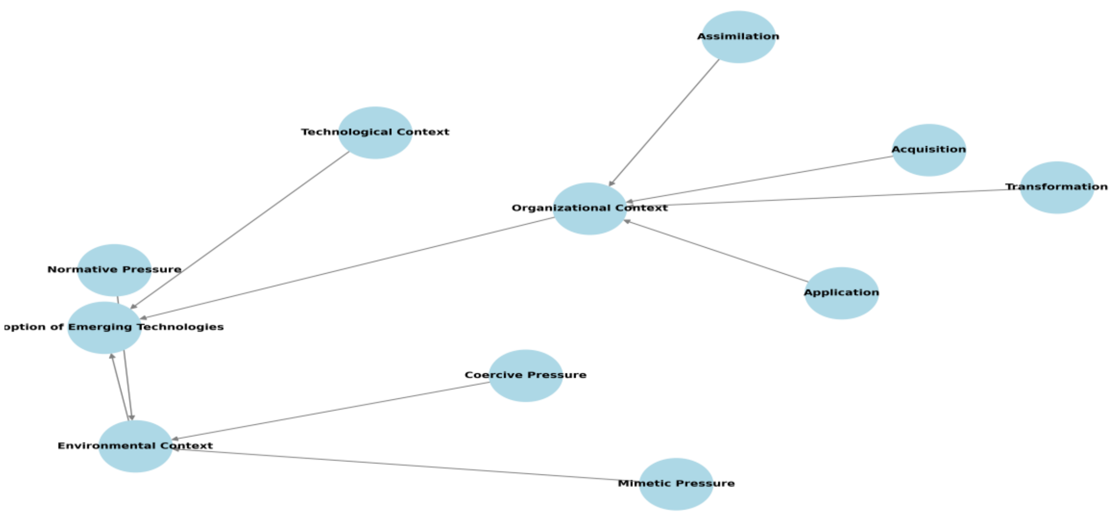


**Figure 1: the theoretical research model**

Table 1. Measurement Items by Context

| Context / Construct | Measurement Item (7-point Likert scale) | Source |
|---|---|---|
| **Technological Context** | Our IT infrastructure is adequate for adopting emerging technologies. | Chan & Chong (2013) |
| **Technological Context** | Our employees are familiar with emerging technologies. | Chan & Chong (2013) |
| **Environmental – Coercive Pressure** | Regulators expect our firm to adopt emerging auditing technologies. | Liang et al. (2007) |
| **Environmental – Normative Pressure** | Our suppliers increasingly adopt emerging technologies. | Liang et al. (2007) |
| **Environmental – Mimetic Pressure** | Competitors perceive adoption of emerging auditing technologies positively. | Liang et al. (2007) |
| **Organizational – Acquisition** | Our firm frequently seeks information about emerging technologies. | Flatten et al. (2011) |
| **Organizational – Assimilation** | Employees are encouraged to absorb new knowledge on technology adoption. | Flatten et al. (2011) |
| **Organizational – Transformation** | Employees transform internal and external knowledge into new insights. | Flatten et al. (2011) |
| **Organizational – Application** | Our firm regularly reconsiders and adapts emerging technologies. | Flatten et al. (2011) |
| **Adoption of Emerging Technologies** | Our firm uses RPA, Blockchain, and Audit Data Analytics (ADA). | Venkatesh & Bala (2012) |

Table 2. Reliability and Validity of Constructs

| Construct | Cronbach's Alpha | Composite Reliability | AVE |
|---|---|---|---|
| **Technological Context** | 0.932 | 0.914 | 0.78 |
| **Environmental – Coercive** | 0.776 | 0.841 | 0.67 |
| **Environmental – Normative** | 0.803 | 0.847 | 0.67 |
| **Environmental – Mimetic** | 0.711 | 0.768 | 0.55 |
| **Organizational – Acquisition** | 0.827 | 0.806 | 0.59 |
| **Organizational – Assimilation** | 0.785 | 0.797 | 0.68 |
| **Organizational – Transformation** | 0.844 | 0.836 | 0.70 |
| **Organizational – Application** | 0.966 | 0.969 | 0.91 |
| **Adoption of Emerging Technologies** | 0.897 | 0.908 | 0.71 |

Table 3. Structural Model Results (PLS-SEM)

| Path | β | t-value | p-value | $R^2$ |
|---|---|---|---|---|
| **Technological Context → Adoption** | 0.673 | 4.758 | 0.000* | 0.645 |
| **Environmental Context → Adoption** | 0.341 | 6.648 | 0.019** | 0.158 |
| **Organizational Context → Adoption** | 0.787 | 6.830 | 0.000* | 0.783 |

### 4.5. Ethical Considerations

All responses were collected anonymously, ensuring confidentiality and voluntary participation. Ethical approval was obtained from the institutional review board of the authors' affiliated university. Given the sensitivity of data in auditing practices, participants were assured that their responses would only be used for academic research purposes.

## 5. Results and Discussion

### 5.1. Measurement Model Evaluation

The reliability and validity of the constructs were confirmed prior to hypothesis testing. All constructs achieved Cronbach's Alpha values above the 0.70 threshold, and Composite Reliability (CR) exceeded 0.80, confirming internal consistency. Convergent validity was established with Average Variance Extracted (AVE) greater than 0.50 across all constructs, while discriminant validity was confirmed using the Fornell–Larcker criterion and HTMT ratios, both indicating adequate construct independence. These results align with recent recommendations for PLS-SEM analysis in accounting and information systems research (Hair et al., 2021; Sarstedt et al., 2022; Fornell & Larcker, 1981).

### 5.2. Structural Model Results

The structural model demonstrated substantial explanatory power, with $R^2$ values exceeding 0.60 for the adoption of emerging technologies (ATE). Path analysis revealed the following:

• Technological context (H1): Strong positive influence on adoption ($\beta = 0.67$, $p < 0.001$), supporting findings by Zhu & Kraemer (2005) and Tsou & Hsu (2015).

• Environmental pressures (H2): Moderate positive influence, particularly normative pressures from clients and regulators ($\beta = 0.34$, $p < 0.05$), consistent with the institutional theory perspectives of Dimaggio & Powell (1983) and Liang et al. (2007).

• Organizational context (H3): The strongest predictor of adoption, reflecting the role of absorptive capacity and leadership support ($\beta = 0.79$, $p < 0.001$), which reinforces the foundational work of Zahra & George (2002) and Cohen & Levinthal (1990).

These findings reinforce the view that while technology readiness and environmental forces matter, the organizational dimension—especially absorptive capacity and digital culture—is the most critical determinant of adoption in auditing practices (Flatten et al., 2011; Ali & Park, 2016).

### 5.3. Discussion of Findings

The results confirm and extend the Technology–Organization–Environment (TOE) framework in the context of auditing (Tornatzky & Fleischer, 1990; Baker, 2012). The strong impact of organizational capabilities highlights the importance of leadership, training, and cross-departmental collaboration in facilitating digital adoption. This is consistent with Flatten et al. (2011) and more recent evidence from Martins & Oliveira (2023), which emphasize absorptive capacity as a key enabler of innovation.

The moderate role of environmental pressures suggests that while regulatory and competitive forces push firms toward digital transformation, external pressures alone are insufficient to ensure deep adoption (Rosli et al., 2016; Oliveira et al., 2019). Instead, firms that integrate external expectations with internal capabilities achieve higher adoption levels, echoing findings by Rahman & Alsmadi (2022) on institutional pressures in technology adoption.

Technological readiness remains significant, especially given the increasing importance of Audit Data Analytics (ADA), AI, and Blockchain in enhancing audit quality (Brown-Liburd & Vasarhelyi, 2015; Vasarhelyi et al., 2015; Pimentel & Boulianne, 2020). Case studies reinforce this:

• WestRock (Deloitte WSJ, 2024): Successfully integrated Generative AI into internal audit, achieving efficiency gains and stronger risk detection.

• KPMG (2024): Reported that 60% of Australian firms use AI in financial processes, demonstrating normative pressures from clients and industry peers (Glover et al., 2014; Teo et al., 2003).

•EY (Financial Times, 2024): Leveraged AI-powered fraud detection tools, reducing detection time and improving audit precision (Ding et al., 2020; Sun, 2019).

### 5.4. Implications for Practice

The findings suggest several implications:

1. For practitioners: Audit firms must invest not only in technology but also in organizational learning and culture to fully capture the benefits of digital auditing.

2. For regulators: Policies should encourage not only compliance with digital tools but also provide incentives for organizational training and digital literacy.

3. For academia: Future research should integrate TOE with Dynamic Capabilities Theory to capture how firms sense and adapt to emerging audit technologies in rapidly evolving environments (Wamba et al., 2023).

## 6. Conclusion and Future Research

This study examined the adoption of emerging technologies in auditing through the Technology–Organization–Environment (TOE) framework, using PLS-SEM to empirically test the influence of technological readiness, organizational capabilities, and environmental pressures. The results confirm that organizational context, particularly absorptive capacity and leadership support, exerts the strongest effect on adoption. Technological readiness also plays a significant role, while environmental pressures exert a moderate yet important influence.

### 6.1. Practical Implications

For practitioners, the findings underscore the necessity of aligning technological investments with organizational culture and training (Zahra & George, 2002; Youssef et al., 2015). Audit firms that foster digital literacy, encourage cross-functional knowledge-sharing, and develop dynamic capabilities are better positioned to leverage AI, Blockchain, RPA, and Audit Data Analytics (ADA) (Cooper et al., 2019; Huang & Vasarhelyi, 2019; Santos et al., 2020). For regulators, the study highlights the importance of designing policy frameworks that not only enforce digital compliance but also incentivize firms to cultivate the human and organizational competencies required for effective adoption (Barr-Pulliam et al., 2021; Barr-Pulliam et al., 2022). For professional associations, such as IFAC and PCAOB, the results suggest the need to update audit guidelines to integrate continuous auditing and AI-enabled assurance practices (AICPA, 2014; Salijeni et al., 2019).

### 6.2. Theoretical Contributions

From a theoretical perspective, the study extends the TOE framework by integrating insights from institutional theory (coercive, normative, and mimetic pressures) and dynamic capabilities theory (Dimaggio & Powell, 1983; Bradley et al., 2011). This hybrid perspective captures how firms not only respond to external pressures but also develop adaptive capabilities that enable sustained use of disruptive audit technologies (Wamba et al., 2023; DePietro et al., 1990). In doing so, the study contributes to ongoing debates about the future of the auditing profession in the digital era, emphasizing the interaction between structural determinants and organizational agility.

### 6.3. Limitations and Future Research

This study is not without limitations. Firstly, the data relies on self-reported perceptions, which may introduce social desirability bias. Future research could benefit from objective adoption metrics. Secondly, the sample, while robust, is from a single regulated environment; comparative studies across different countries could uncover cultural and regulatory nuances (Amorim et al., 2012). Future studies should also integrate other theoretical lenses, such as the Diffusion of Innovation Theory (DOI), to further understand the technological context, and employ qualitative methods to gain deeper insights into the implementation challenges and success factors of emerging technologies in audit practices. Finally, as technologies evolve, longitudinal studies will be crucial to understand the long-term impact of these adoptions on audit quality and efficiency.

### 6.4. Final Reflection

The findings suggest that the auditing profession is undergoing a fundamental transformation. By embracing digital innovation, auditors can transition from compliance-oriented tasks to strategic value creators, providing real-time insights that strengthen governance, accountability, and stakeholder trust. However, realizing this vision requires balancing technological innovation with organizational adaptation and ethical responsibility. As the profession enters the era of AI-augmented auditing, collaboration among practitioners, regulators, and researchers will be essential to ensure that emerging technologies enhance—not compromise—the credibility and reliability of the audit function.

## References

Al-Htaybat, K., & Von Alberti-Alhtaybat, L. (2017). Big Data and corporate reporting: impacts and paradoxes. Accounting, Auditing & Accountability Journal, 30(4), 850–873. https://doi.org/10.1108/AAAJ-07-2015-2139

Ali, M., & Park, K. (2016). The mediating role of an innovative culture in the relationship between absorptive capacity and technical and non-technical innovation. Journal of Business Research, 69(5), 1669–1675. https://doi.org/10.1016/j.jbusres.2015.10.036

Appelbaum, D., & Nehmer, R. A. (2017). Using drones in internal and external audits: An exploratory framework. Journal of Emerging Technologies in Accounting, 1, 99–113. http://10.2308/jeta-51704

Arpaci, I., Yardimci, Y. C., Ozkan, S., & Turetken, O. (2012). Organizational, adoption of information technologies: a literature review. International Journal of eBusiness and eGovernment Studies, 4(2), 37–50.

Austin, A., Carpenter, T, Christ, M & Nielson, C. (2019). The data analytics transformation: Evidence from auditors, CPOs, and standard-setters. SSRN. http://10.2139/ssrn.3214140

Baron, R. M., & Kenny, D. A. (1986). The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. Journal of Personality and Social Psychology, 51(6), 1173–1182. DOI: 10.1037//0022-3514.51.6.1173

Barr-Pulliam, D., Brown-Liburd, H. L., & Sanderson, K. A. (2021). The effects of the internal control opinion and use of audit data analytics on perceptions of audit quality, assurance, and auditor negligence. Auditing: A Journal of Practice and Theory, 41(1), 25–48. https://doi.org/10.2308/AJPT-19-064

Bradley, S. W., Shepherd, D. A., & Wiklund, J. (2011). The importance of slack for new organizations facing 'tough' environments. Journal of Management Studies, 48(5), 1071–1097. https://doi.org/10.1111/j.1467-6486.2009.00906.x

Brown-Liburd, H., & Vasarhelyi, M. (2015). Big Data and Audit Evidence. Journal of Emerging Technologies in Accounting, 12(1), 1–16. https://10.2308/jeta-10468

Carpenter, V. L., & Feroz, E. H. (2001). Institutional theory and accounting rule choice: An analysis of four US state governments' decisions to adopt generally accepted accounting principles. Acc. Organ. Soc., 26(7), 565–596. https://doi.org/10.1016/S0361-3682(00)00038-6

Cohen, W., & Levinthal, D. (1990). Absorptive capacity, a new perspective on learning and innovation, Admin. Sci. Quart, 35(1), 128–152. https://doi.org/10.2307/2393553

Cooper, L. A., Holderness, D. K., Sorensen, T. L., & Wood, D. A. (2019). Robotic Process Automation in Public Accounting. Accounting Horizons, 33(4), 15–35. http://dx.doi.org/10.2139/ssrn.3193222

Coraiola, D. M, & Machado-da-Silva, C. L. (2008). A influência dos discursos no isomorfismo organizacional: as mudanças gráficas em jornais brasileiros. Revista Eletrônica de Ciência Administrativa, 7(2), 1-13.

Cruz-Jesus, F., Pinheiro, A., & Oliveira, T. (2019) Understanding CRM adoption stages: Empirical analysis building on the TOE framework. Computers in Industry 109: 1–13. https://doi.org/10.1016/j.compind.2019.03.007

Dagliene, L., & Kloviené, L. (2019). Motivation to use big data and big data analytics in external auditing. Managerial Auditing Journal, 34(7), 750–782. https://doi.org/10.1108/MAJ-01-2018-1773

Dedoulis, E. (2016). Institutional formations and the Anglo-Americanization of local auditing practices: The case of Greece. Accounting Forum, 40(1), 29–44. https://doi.org/10.1016/j.accfor.2015.11.003

Deloitte. (2024). How WestRock harnessed GenAI to enhance internal audit. Deloitte WSJ.

Dimaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. American Sociological Review, 48(2), 147–160. https://doi.org/10.2307/2095101

Ding, K., Peng, X., Lev, B., Sun, T., & Vasarhelyi, M. A. (2020). Machine Learning Improves accounting estimates: evidence from insurance payments. Review of Accounting Studies 25, 1098-1123. https://doi.org/10.1007/s11142-020-09546-9

Eilifsen, A., Kinserdal, F, Messier Jr & Mckee, T. E. (2020). An exploratory study into the use of audit data analytics on audit engagements. Accounting Horizons, 34(4). http://10.2308/HORIZONS-19-121

EY. (2024). AI-based fraud detection in auditing. Financial Times.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error: algebra and statistics. Journal of Marketing, 18(1), 39-59. https://doi.org/10.2307/3151312

Glover, J. L., Champion, D., Daniels, K. J., & Dainty, A. J. D. (2014). An Institutional Theory perspective on sustainable practices across the dairy supply chain. International Journal of Production Economics, 152, 102-111. https://doi.org/10.1016/j.ijpe.2013.12.027

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Danks, N. (2021). Partial least squares structural equation modeling (PLS-SEM) using R. Springer. https://doi.org/10.1007/978-3-030-80519-7

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., & Thomas, G. N. (2021). How audit firm size moderate effect of TOE context toward auditor adoption of technology. Turkish Journal of Computer and Mathematics Education, 12(6), 1518-1526.

Henseler, J., & Fassott, G. (2010). Testing Moderating Effects in PLS Path Models: An Illustration of Available Procedures. Handbook of Partial Least Squares, 713-735.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. Information and Organization, 28(1), 52–61. https://doi.org/10.1016/j.infoandorg.2018.02.004

Huang, F., & Vasarhelyi, M. A. (2019). Applying robotic process automation (HUU) in auditing: A framework. International Journal of Accounting Information Systems, 35, 1-11. https://doi.org/10.1016/j.accinf.2019.100433

Inghirami, I. E. (2018). Accounting Information Systems in the Time of Blockchain. Pávia: ITAIS Conference.

KPMG. (2024). Most Australian companies now using AI for financial processes. The Australian.

Kroon, N., Alves, M. C., & Martins, I. (2021). The Impacts of Emerging Technologies on Accountants' Role and Skills: Connecting to Open Innovation—A Systematic Literature Review. Journal of Open Innovation: Technology, Market, and Complexity, 7(3), 2021. https://doi.org/10.3390/joitmc7030163

Li, Q., & Vasarhelyi, M. (2018). Developing a Cognitive Assistant for the Audit Plan Brainstorming Session. The International Journal of Digital Accounting Research, 18, 119–140. https://doi.org/10.4192/1577-8517-v18_5

Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. Industrial management & data systems, 111(7), 1006-1023. https://doi.org/10.1108/02635571111161262

Martins, R., & Oliveira, T. (2023). Digital literacy, absorptive capacity, and technology adoption in organizations. Information Systems Frontiers. https://doi.org/10.1007/s10796-023-10427-9

Moffitt, K. C., Rozario, A. M., & Vasarhelyi, M. A. (2018). Robotic process automation for auditing. Journal of Emerging Technologies in Accounting, 15(1), 1–10. DOI: 10.2308/jeta-10589

Montes, G. A., & Goertzel, B. (2019). Distributed, decentralized, and democratized artificial intelligence. Technological Forecasting and Social Change,141, 354-358. https://doi.org/10.1016/j.techfore.2018.11.010

Oliveira, T., Martins, R., Sarker, S., Thomas, M., & Popovic, A. (2019). Understanding SaaS adoption: The moderating impact of the environment context. International Journal of Information Management, 49, 1-12. https://doi.org/10.1016/j.ijinfomgt.2019.02.009

PCAOB & IFAC. (2024). Guidelines on auditing standards and technology adoption.

Pimentel, E., & Boulianne, E. (2020). Blockchain in Accounting Research and Practice: Current Trends and Future. Opportunities. Accounting Perspectives, 19(4), 325-361. https://doi.org/10.1108/AAAI-10-2020-4991

Pivar, J. (2021) Adoption of big data technologies in smart cities of the European Union: Analysis of the importance and performance of technological factors. Croatian Regional Development Journal, 2(1), 11-29. DOI:10.2478/crdj-2021-0005

Rahman, M. M., & Alsmadi, M. K. (2022). Institutional pressures and technology adoption: Evidence from developing countries. Technological Forecasting & Social Change, 182, 121841. https://doi.org/10.1016/j.techfore.2022.121841

ResearchGate. (2025). Technology adoption factors for Supreme Audit Institutions. Retrieved from https://www.researchgate.net/publication/387487360

Rosli, K., Siew, E.G., & Yeow, P. H. P. (2016). Technological, Organizational and Environmental Aspects of Audit Technology Acceptance. International Journal of Business and Management, 11(5), 140-145. Doi: 10.5539/ijbm.v11n5p140

Rozario, A. M., & Vasarhelyi, M. A. (2019a). Auditing with smart contracts. International Journal of Digital Accounting Research, 18(1), 1-27. https://doi.org/10.4192/1577-8517-v18_1

Rozario, A. M., & Vasarhelyi, M. A. (2019b). How robotic process automation is transforming accounting and auditing. The CPA Journal, 88, 46-49. https://doi.org/10.20869/AUDITF/2020/160/024

Salijeni, G., Samsonova-Taddei, A., & Turley, S. (2019). Big Data and Changes in Audit Technology: Contemplating a Research Agenda. Accounting and Business Research, 49(1), 95-119. https://doi.org/10.1080/00014788.2018.1459458

Sancho-Zamora, R., Hernandez-Perlines, F., Pena-Garcia, I., & Gutierrez-Broncano, S. (2022). The Impact of Absorptive Capacity on Innovation: The Mediating Role of Organizational Learning. International Journal of Environment Research and Public Health, 19(2), 842. https://doi.org/10.3390/ijerph19020842

Santos, F., Pereira, R., & Vasconcelos, J. B. (2020). Toward robotic process automation implementation: an end-to-end perspective. Business Process Management Journal, 26(2), 405-420. https://doi.org/10.1108/BPMJ-12-2018-0380

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). Partial least squares structural equation modeling: A useful tool for family business researchers. Journal of Family Business Strategy, 13(1), 100521. https://doi.org/10.1016/j.jfbs.2021.100521

Scott, W. (2003). Organisation: Rational, Natural, and Open System (5th ed.). Upper Saddle River, NJ: Prentice Hall.

Siew, E.G., Rosli, K., & Yeow, P.H.P. (2019). Organizational and environmental influences in the adoption of computer-assisted audit tools and tec. International Journal of Accounting Information Systems, 36, 100445. https://doi.org/10.1016/j.accinf.2019.100445

Singh, A., Gupta, S., & Sharma, R. (2023). TOE framework and adoption of digital technologies in auditing. Journal of Business Research, 161, 113810. https://doi.org/10.1016/j.jbusres.2023.113810

Sun, T. (2019). Applying Deep Learning to Audit Procedures: An Illustrative Framework. Accounting Horizons, 33(3), 89-109. https://doi.org/10.2308/acch-52455

Tajudeen, F. P., Jaafar, N. I., & Ainin, S. (2017). Understanding the Impact of Social Media Usage among Organizations. Information & Management, 55(2018), 308–321. https://doi.org/10.1016/j.im.2017.08.004

Tornatzky, L. G., & Fleischer, M. (1990). The Processes of Technological Innovation. Lexington – MA: Lexington Books.

Tsou, H.-T., & Hsu, S. H.-Y. (2015). Performance effects of technology–organization–environment openness, service co-production, and digital-resource readiness: The case of the IT industry. International Journal of Information Management, 35(1), 1-14. https://doi.org/10.1016/j.jiinfomgt.2014.09.001

Vasarhelyi, M. A., Kogan, A., & Tuttle, B. M. (2015). Big data in accounting: An overview. Accounting Horizons, 29(2), 381-396. https://doi.org/10.2308/acch-51071

Vitali, M. (2024). Artificial intelligence in auditing: Opportunities and challenges. Journal of Emerging Technologies in Accounting, 21(2), 45–63. Elsevier. https://doi.org/10.1016/j.accinf.2024.100637

Wamba, S. F., Dubey, R., & Gunasekaran, A. (2023). Dynamic capabilities and digital transformation: Implications for auditing. International Journal of Information Management, 70, 102572. https://doi.org/10.1016/j.ijinfomgt.2023.102572

Warren, J. D., Moffitt, K. C., & Byrnes, P. (2015). How big data will change accounting. Accounting Horizons, 29(2), 397–407. https://doi.org/10.2308/acch-51069

White, B. S., King, C. G., & Hollada, J. (2020). Blockchain security risk assessment and the auditor. Journal of Corporate Accounting & Finance, 31(2), 47–53. https://doi.org/10.1002/jcaf.22433

Widuri, R., Oconnell, B., & Yapa, P. W. W. (2019). Adopting generalized audit software: an Indonesian perspective. Managerial Auditing Journal, 31(8/9), 821-847. https://doi.org/10.1108/MAJ-10-2015-1247

Witte, A. L. (2020). Technology Based Audit Tools: Implications for Audit Quality (Tese de doutorado, Setor de Contabilidade, Bentley University). https://scholars.bentley.edu/cgi/viewcontent.cgi?article=1000&context=etd_2020

Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: cross-country evidence from the retail industry. Information systems Research, 16(1), 61–84. https://doi.org/10.1287/isre.1050.0045