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Determinants of artificial intelligence adoption in audit firms: an immersion in theoretical approaches and a proposed conceptual framework

Facteurs déterminants d'adoption de l'intelligence artificielle dans les cabinets d'audit : immersion dans les approches théoriques et proposition d'un cadre conceptuel

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Abstract

With the rapid rise of artificial intelligence (AI), organizations are racing to leverage its benefits, prompting research into the factors influencing its adoption. This article explores the determinants of AI adoption in audit firms using an integrated model combining the TOE framework, Diffusion of Innovations (DOI) theory, and institutional theory. It aims to identify both drivers and barriers shaping decisions to implement AI, considering technological, organizational, and environmental contexts. Technologically, DOI highlights factors such as complexity, compatibility, and relative advantage. Organizationally, the TOE framework emphasizes firm size, management support, and readiness. Externally, institutional theory explains pressures from competition, regulation, and professional expectations. By integrating these perspectives, the study provides a comprehensive understanding of AI adoption in audit firms and establishes a strong conceptual basis for future empirical research.

Keywords: TOE framework; artificial intelligence; audit firm; DOI theory; institutional theory.

Résumé

Avec l'essor rapide de l'intelligence artificielle (IA), les organisations se livrent à une course effrénée pour tirer parti de ses avantages, ce qui a suscité des recherches sur les facteurs influençant son adoption. Cet article explore les déterminants de l'adoption de l'IA dans les cabinets d'audit à l'aide d'un modèle intégré combinant le cadre TOE, la théorie de la diffusion des innovations (DOI) et la théorie institutionnelle. Il vise à identifier à la fois les facteurs favorables et les obstacles qui façonnent les décisions de mise en œuvre de l'IA, en tenant compte des contextes technologiques, organisationnels et environnementaux. Sur le plan technologique, la DOI met en avant des facteurs tels que la complexité, la compatibilité et l'avantage relatif. Sur le plan organisationnel, le cadre TOE met l'accent sur la taille de l'entreprise, le soutien de la direction et l'état de préparation. Sur le plan externe, la théorie institutionnelle explique les pressions exercées par la concurrence, la réglementation et les attentes professionnelles. En intégrant ces perspectives, l'étude offre une compréhension globale de l'adoption de l'IA dans les cabinets d'audit et établit une base conceptuelle solide pour de futures recherches empiriques.

Mots clés : cadre TOE ; Intelligence artificielle ; cabinet d'audit ; théorie DOI ; théorie institutionnelle.

Introduction

In recent years, the adoption of emerging technologies has become a major challenge for individuals and organizations (Roztocki et al., 2019), particularly in an environment shaped by digital transformation and the development of revolutionary technologies such as artificial intelligence. Studying the mechanisms underlying this adoption is thus a central issue in management science and information systems (Z. Xu et al., 2021).

Technology adoption cannot be studied one-dimensionally; it requires distinguishing between individual- and organizational-level frameworks (Pillai & Sivathanu, 2020). At the individual level, adoption models focus on users' perceptions and attitudes, such as expected effort, ease of use, behavioral intentions, or perceived utility (Daoud, 2023; Mohamed et al., 2019; Pedrosa et al., 2020). In contrast, the organizational approach considers structural, environmental, strategic, and organizational factors (Taherdoost, 2018). This distinction is evident in recent scientific studies, in that organizational decisions regarding technological innovation go beyond individual acceptance mechanisms to encompass institutional barriers, financial resources, and competitive pressures (Amade et al., 2020).

Following this line of reasoning, a wide range of theoretical frameworks has been employed to highlight the conditions for technological innovation. The TOE (Technology-Organization-Environment) framework, the theory of diffusion of innovations (DOI), and institutional theory are among the most influential theories (Prasad Agrawal, 2024). The TOE framework highlights the contexts in which a new technology is implemented. It is based on a multidimensional approach that integrates technological, organizational, and environmental dimensions, thereby offering a scientific methodology specifically designed for empirical analyses at the firm level (Simina & Dutescu, 2024). The DOI theory, for its part, focuses on the specific characteristics of the technology and their impact on the diffusion process (Oliveira & Martins, 2011). Finally, institutional theory completes the analytical framework by emphasizing the pressures exerted by the external environment on organizations (Amade et al., 2020).

Researchers are working to integrate these theories in order to develop complementary analytical models capable of better capturing the ambiguity surrounding technology adoption. For example, the literature includes several studies demonstrating that combining the TOE with the DOI (Chen et al., 2021; Liu & Cao, 2022; Sajja & Meesala, 2024) helps identify not only the characteristics of the technology but also the internal factors underlying its adoption, particularly in the context of SMEs and digital innovations (Faiz et al., 2024). However, the combination of TOE with institutional theory (Elghdban et al., 2023; Gibbs & Kraemer, 2004) helps identify the pressures firms face in their digital transformation.

Literature highlights studies on AI adoption using the TOE framework (Alarefi, 2024; Badghish & Soomro, 2024; Felemban et al., 2024; Nguyen et al., 2022; Paiva, 2024; Sajja & Meesala, 2024). However, research on factors influencing AI integration in audit firms using the TOE framework is scarce. Only a few studies have explored this area, including Seethamraju & Hecimovic (2023) and Yang et al. (2024) in Australia, and Simina & Dutescu (2024) in Europe. In Morocco, no studies have yet addressed this field of study.

Based on these elements, this research article aims to develop a conceptual model for understanding the adoption of AI technology within audit firms by drawing on the TOE framework, the DOI, and institutional theory. These theories form a theoretical interdependence, which supports our choice of a conceptual foundation that integrates these three approaches in the present study. This model leads to the identification of explanatory variables within the technological, organizational, and environmental contexts. Consequently, hypotheses will be formulated to guide the empirical testing of the relationships between these variables and the adoption of AI. Thus, our study contributes to the literature by suggesting a multidimensional approach to the adoption of a revolutionary technology such as AI, while presenting a powerful analytical framework for examining organizational decisions related to new technologies. This will allow us to address the following research question: « ***To what extent do technological, organizational, and environmental factors determine the adoption of AI within audit firms in Morocco?*** »

Our study will be divided into three main sections. The first section will highlight the various theoretical approaches used in studies on the adoption of new technologies, while justifying our choice of research methodology. The second section will present the theoretical frameworks selected for the research, explaining their origins and foundations. Finally, the third and last section will be dedicated to identifying the factors influencing AI adoption in audit firms, while developing the hypotheses and outlining the conceptual model of the research.

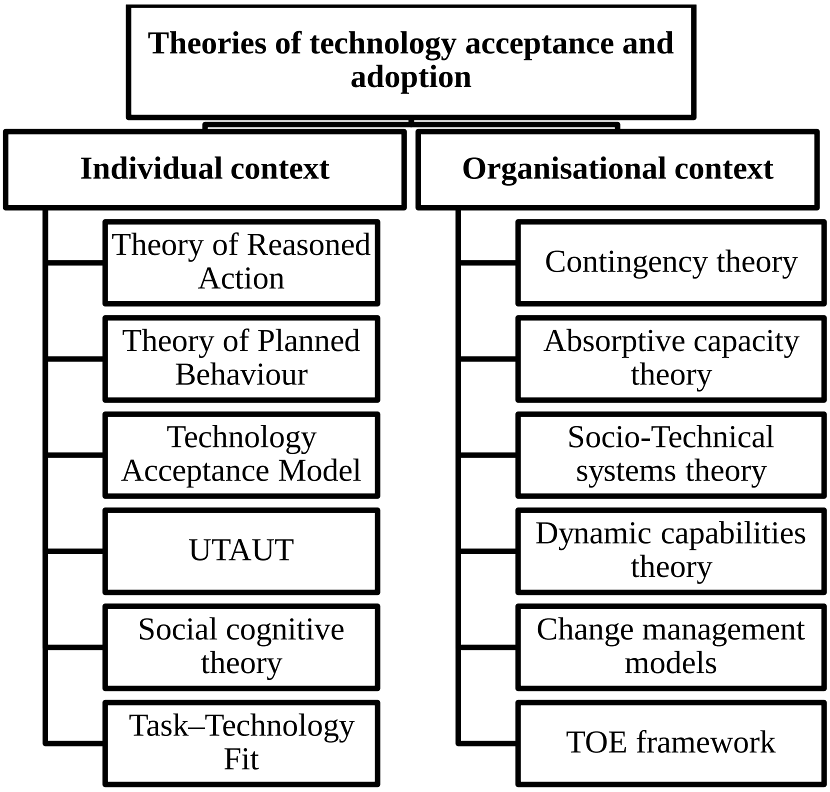
1. Theoretical approach of the research

1.1. Different theoretical approaches to the adoption of new technologies

The adoption of a technology is influenced by several key factors that researchers have sought to identify through various theoretical models. However, some theories explain technology adoption at the **individual level**, while others explain it at the **organizational level** (**Erreur !**

Source du renvoi introuvable.). Theories of the first type examine an individual's acceptance of an innovation, based on purely psychological factors. In contrast, those of the second type explain an organization's decision to adopt a technological tool.

Figure N°1: Examples of theories on the adoption of new technologies



Source: Authors

1.2. Selection of the theoretical research approach

Theoretical models such as TAM, TRA, TPB, and UTAUT focus on individual attitudes toward technology, measurable only after adoption. They do not identify organizational factors influencing the decision to adopt an innovation beforehand. Therefore, an individual-level approach is not suitable for studying factors affecting AI adoption in audit firms, for several reasons:

- <u>The nature of technology adoption:</u> Organizational technology adoption differs from individual adoption, as it is not merely a personal choice but a strategic decision requiring adequate resources and prior preparation (Khanfar et al., 2024; Tursunbayeva & Chalutz-Ben Gal, 2024). It also depends on the firm's governance structure and organizational readiness. Rather than focusing on individual attitudes, it is more relevant to examine macro-level factors (technological, organizational, and environmental) that shape adoption (Kurup & Gupta, 2022; Selten & Klievink, 2024).

- Organizational adaptability to the environment: Organizational theory emphasizes that firms must adapt to their environment to survive (Arunga, 2023). AI adoption involves both internal and external stakeholders (Badghish & Soomro, 2024). Its effectiveness depends on client data acceptance, competitive advantage (Yang et al., 2024), and compliance with legal requirements on personal data (Heimberger et al., 2024; Yang et al., 2024).
- General dimension of the organizational context: Analyzing AI adoption at the organizational level involves a multi-stage collective process: (1) awareness, (2) evaluation, (3) decision-making, (4) implementation, and (5) diffusion across the organization. This transformation requires the involvement of both internal and external stakeholders, as well as strategic alignment and institutional support (Badghish & Soomro, 2024; Hradecky et al., 2022; Trunk et al., 2020)

  However, models such as TAM and UTAUT do not fully capture this complexity (Venkatesh, 2022). Studying AI adoption in Moroccan audit firms thus requires frameworks addressing adoption at the organizational level.
- The Evolving Landscape of AI Technology: AI development differs across countries due to the extensive infrastructure it requires (Mubarok et al., 2025). Leading tech nations benefit from strong financial, human, and technical resources, creating gaps between firms and countries (Wang et al., 2024). While some countries have clear AI strategies (Salas-Pilco, 2019), Morocco lacks a structured plan, sufficient R&D support, and an adequate legal framework (Lafram & Bahji, 2024). Consequently, AI adoption in Moroccan audit firms is still nascent, supporting an organizational-level focus.

In our research, we have chosen to focus on the **organizational approach** when examining the determinants of AI adoption. However, since a variety of theoretical frameworks that explain the integration of innovation into an organization, exist, it would be best to explain the theoretical foundation we have chosen, while also providing justification for our choice.

2. Theoretical framework of the research

Our research requires a holistic approach to identify factors influencing AI adoption in Moroccan audit firms at the technological, organizational, and environmental levels. The primary framework selected is the **Technology-Organization-Environment « TOE » framework** (DePietro et al., 1990).

To address its limitations, TOE is combined with the **Diffusion Of Innovations theory** to explain technological factors (Rogers, 1962, 1995) and with **institutional theory** to capture environmental variables (DiMaggio & Powell, 1983). This section presents the TOE model's foundations and the complementary theories used to address its gaps.

2.1. TOE Framework

The TOE framework, which stands for « Technology-Organization-Environment », addresses technology adoption at the organizational level. Introduced in « *The Processes of Technological Innovation* », edited by Tornatzky and Fleischer and published in 1990. In a chapter of this book titled ''The Context for Change: Organization, Technology, and Environment'', DePietro et al. (1990) explain that adoption is shaped by internal and external contexts, including technological infrastructure, organizational structure, and environmental conditions. The framework has strong empirical support and helps identify variables that facilitate technology integration (Baker, 2012; Oliveira & Martins, 2011).

The three components of this framework are defined as follows:

- **Technological context:** Refers to internal and external technologies relevant to the firm, including available resources, equipment, and practices, as well as external technologies not yet adopted but potentially usable.
- **Organizational context:** Covers the firm's characteristics, including size, managerial structure, internal communication, and human resources.
- **Environmental context:** Encompasses the firm's external environment, including competitors, industry stakeholders, customers, suppliers, and government relations.

The TOE framework provides an overview of the broader context enabling technology implementation within organizations and offers a useful tool for understanding the adoption of emerging technologies such as AI (Seethamraju & Hecimovic, 2023). It has served as a foundational model in studies on AI adoption in business (Alarefi, 2024; Badghish & Soomro, 2024; Paiva, 2024; Sajja & Meesala, 2024; Seethamraju & Hecimovic, 2023; Simina & Dutescu, 2024) and in research on various technological innovations (Abed, 2020; Bag et al., 2022; Horani et al., 2023; Marei, 2024; Rosli et al., 2012; Salah & Ayyash, 2023; Stjepić et al., 2021; W. Xu et al., 2017).

Despite its strengths, the TOE model has limitations, as it addresses technology adoption determinants too generally and does not consider the impact of perceptions of a technology's characteristics on adoption (Chatterjee et al., 2021; Toufaily et al., 2021).

To address these gaps, researchers incorporate the characteristics of innovations from DOI (Rogers, 1995) into the TOE framework, providing a more detailed, micro-level perspective on AI's features (Faiz et al., 2024). The evolving nature, variable adoption rates, and complexity of AI make DOI particularly suitable for this model (Almaiah et al., 2022; Handoko et al., 2024).

Similarly, integrating institutional theory improves the justification of environmental factors in TOE by identifying coercive, normative, and mimetic pressures that influence organizational technology adoption (Elghdban et al., 2023; Gürbüz & AlJamal, 2024).

2.2. Diffusion Of Innovations - DOI

First proposed by Everett Rogers (1962) in his book « *Diffusion of Innovations* », this theory is fundamental to studies on the diffusion of various innovations, at both the individual and organizational levels. With its hybrid nature, the DOI, or IDT (Innovation Diffusion Theory) as some researchers call it, explains how, why, and to what extent an innovation spreads within a given environment, using communication channels and following specific stages (J. C. F. Li, 2020).

Rogers (1995b) argues that the rate of adoption of an innovation varies from one technology to another. Similarly, organizations adopt technologies at different paces. This is due to the perceived characteristics that distinguish each of these innovations, prompting their rapid implementation:

- **Relative advantage:** refers to the perceived benefits offered by a new idea when compared to the existing practice it is intended to replace
- **Compatibility:** the perception that an innovation aligns with an individual's values, beliefs, or past experiences
- **Complexity:** an idea is perceived as complex when it is difficult to assimilate or understand
- **Testability:** when an innovation is likely to be tested
- **Observability:** the ease with which the results of an innovation can be noticed by others

Models of individual technology acceptance predict behavior at a specific point in time, whereas DOI theory allows tracing the development of technological innovation and adoption decisions over time, including changes due to communication channels (J. C. F. Li, 2020).

DOI's strength lies in its application to both individual and organizational studies and its combination with the TOE framework to explain the technological context influencing innovation choice. It has been used to study the adoption of business analytics in banking (Horani et al., 2023), AI in supply chains (Sajja & Meesala, 2024), digitalization in SMEs (Faiz et al., 2024), data migration to the cloud (Alkhalil et al., 2017), and cloud computing in SME supply chains (Amini & Jahanbakhsh Javid, 2023).

2.3. Institutional theory

The origins of institutional theory trace back to early modern sociologists such as Émile Durkheim and were further developed from the 1980s. Organizations are not fully free in their decision-making, as their actions are influenced by social, cultural, and legitimacy concerns (Scott & Christensen, 1995). Consequently, firms comply with the rules, pressures, and belief systems of their environment. This theory introduces institutional isomorphism, where firms in the same sector become similar over time, responding to environmental pressures, and is divided into three mechanisms (DiMaggio & Powell, 1983) :

- **Coercive:** formal or informal pressure exerted by regulatory institutions through legislation
- **Mimetic:** imitation of leading competitors in the sector to ensure survival and market position
- **Normative:** collective effort by members of the organization to define their professional practices, rules, and standards

In technology adoption, companies face institutional pressures—mimetic, coercive, or normative—that influence their innovation decisions (Oliveira & Martins, 2011). Firms often mimic leading competitors under uncertainty but adopt innovations quickly to comply with government requirements or satisfy key partners. Implementation can also be driven by professional organizations promoting industry innovation (Soares et al., 2020).

Combining institutional theory with the TOE framework has explained the impact of the external environment on innovation adoption, including Big Data Analytics in supply chains (Mezghani et al., 2022), e-procurement systems in manufacturing (Y. Li, 2008), e-commerce (Gibbs & Kraemer, 2004), virtual world technologies (Yoon & George, 2013), and Industry 4.0 and digital supply chains (Gupta et al., 2020).

3. Determinants of AI Adoption in Audit Firms and the Development of Research Hypotheses

3.1. Technological Factors

3.1.1. Relative Advantage

According to DOI theory, relative advantage is the perceived superiority of an innovation over its predecessors (Rogers, 1995). Technologies with better performance and cost-effectiveness are more likely to be adopted (Badghish & Soomro, 2024), especially when offering operational and strategic value (Simina & Dutescu, 2024). AI, for instance, boosts auditors' efficiency by enabling large-scale data analysis, reducing errors, and cutting time and costs for higher value-added tasks (Seethamraju & Hecimovic, 2023).

A significant relative advantage accelerates innovation adoption (Badghish & Soomro, 2024), and prior studies confirm its positive effect on AI adoption (Felemban et al., 2024; Nguyen et al., 2022; Pillai et al., 2022; Pumplun et al., 2019). In Morocco, AI adoption in audit firms depends on managers' perception of its utility and competitive advantage, leading to the following hypothesis:

H1: Relative advantage has a positive effect on the adoption of AI in audit firms

3.1.2. Complexity

According to the DOI, complexity refers to the difficulty of understanding and using an innovation (Rogers, 1995). Organizations tend to adopt complex technologies only after acquiring sufficient technical knowledge. Factors such as skill shortages, low maturity, high costs, and long development periods increase AI complexity and discourage adoption (Phuoc, 2022). Since complexity varies across applications, its impact on AI adoption remains significant (Badghish & Soomro, 2024).

The likelihood of adoption increases with ease of integration (Chen et al., 2021), while complexity is negatively associated with adoption (Liu & Cao, 2022). Prior studies confirm this negative relationship in the case of AI (AL-khatib, 2023; Badghish & Soomro, 2024; Phuoc, 2022; Zhou, 2023). In this study, AI complexity may hinder its adoption in audit firms, leading to the following hypothesis:

H2: Complexity has a negative impact on the adoption of AI in audit firms

3.1.3. Compatibility

According to Rogers (1995b), compatibility refers to how well an innovation aligns with an organization's past experiences, needs, and values. A technological solution must fit sector-specific characteristics (Simina & Dutescu, 2024), while compatibility facilitates goal achievement and reduces adoption resistance (Pillai et al., 2022). Firms may hesitate to adopt AI if it does not integrate with existing systems, which depends on system nature, integration needs, and intended use (Neumann et al., 2024; Simina & Dutescu, 2024).

Incompatibility can increase time, cost, and effort, as shown by integration challenges requiring additional expertise (Yang et al., 2024), whereas compatibility reduces implementation burden (Nguyen et al., 2022).

The literature identifies compatibility as a key predictor of innovation adoption, with studies confirming its positive effect on AI adoption (Badghish & Soomro, 2024; Liu & Cao, 2022; Paiva, 2024; Phuoc, 2022; Seethamraju & Hecimovic, 2023). These findings lead to the following hypothesis:

H3: Compatibility has a positive impact on the adoption of AI in audit firms

3.2. Organisational factors

3.2.1. Top management support

In organizations, management plays a crucial role in shaping decisions (Liu & Cao, 2022). In this study, management support refers to the involvement of leaders in the adoption of technologies, which is essential for successful implementation (Simina & Dutescu, 2024).

The adoption of AI requires significant organizational changes, including culture, customer acceptance, and resource allocation. Senior management drives this process by promoting change, defining strategies, allocating resources, and overcoming resistance (Neumann et al., 2024). Without such support, AI implementation is unlikely, as technological progress depends on strong leadership (Lim & Seng, 2024)

Prior studies confirm the positive impact of management support on AI adoption (Merhi & Harfouche, 2023; Nguyen et al., 2022; Sharma et al., 2023; Tan et al., 2022; Yang et al., 2024), as it fosters a favorable environment for technological transformation. This relationship leads to the following hypothesis:

H4: Top management support has a positive effect on the adoption of AI in audit firms

3.2.2. Organizational Readiness

Organizational readiness requires human skills, financial resources, and technical infrastructure (Paiva, 2024). In the AI era, training existing staff is often more effective than hiring scarce, costly specialists (Pumplun et al., 2019).

This shift is evident in audit firms, where professionals are increasingly expected to combine accounting, programming, and data skills, enabling them to interpret AI outputs while maintaining judgment and skepticism (Seethamraju & Hecimovic, 2023).

Financial resources remain a key enabler, as AI adoption requires significant investment, although financial constraints often lead to innovation failure (Felemban et al., 2024; Lim & Seng, 2024; Liu & Cao, 2022). Additionally, a strong technical infrastructure is essential but can be costly to acquire and maintain (Pillai et al., 2022).

The impact of organizational readiness on AI adoption has been widely confirmed in prior studies (AL-khatib, 2023; Lim & Seng, 2024; Phuoc, 2022; Simina & Dutescu, 2024), leading to the following hypothesis:

H5: Organizational readiness has a positive effect on the adoption of AI in audit firms

3.2.3. Firm Size

Organizational size, measured by the number of employees, reflects a firm's structure, resources, and capital. Larger firms face fewer barriers in the early stages of technology adoption, as they can invest in infrastructure, training, and risk management, and leverage networks with technology providers. Their abundant resources and capabilities allow them to experiment with AI, absorb initial costs, and manage potential implementation challenges more effectively, giving them a clear advantage over smaller firms (Pan et al., 2023).

Large companies possess the technical, financial, and human resources to adopt innovations, absorb initial AI investments, manage risks, and collaborate with suppliers to develop AI solutions (Simina & Dutescu, 2024). They adopt AI faster and more extensively than other innovations, often supported by a large customer base (Phuoc, 2022; Pumplun et al., 2019).

The TOE framework highlights firm-specific characteristics such as size as key determinants of innovation adoption (DePietro et al., 1990). Studies on AI adoption using this framework have examined the effect of size on organizational decisions (Neumann et al., 2024; Nguyen et al., 2022; Prasad Agrawal, 2024; Simina & Dutescu, 2024), leading to the following hypothesis:

H6: Firm Size has a positive effect on the adoption of AI in audit firms

3.3. Environmental factors

3.3.1. Competitive pressure

Technological innovation is often driven by competitive pressure, as firms adopt new technologies to maintain market position (Chen et al., 2021). This mimetic force, explained by institutional theory (DiMaggio & Powell, 1983), pushes organizations to follow competitors' innovations (Gupta et al., 2022). AI adoption can enhance a firm's offerings, competitive advantage, and reputation (Phuoc, 2022).

In the audit sector, competitive pressure impacts firms differently: small firms adopt AI to differentiate themselves, medium-sized firms to gain efficiency and reduce costs, while large firms are less influenced, focusing on regulatory incentives (Yang et al., 2024).

The effect of competitive pressure on AI adoption has been extensively studied (Lim & Seng, 2024; Merhi & Harfouche, 2023; Paiva, 2024; Sharma et al., 2023), leading to the following hypothesis:

H7: Competitive pressure has a positive effect on the adoption of AI in audit firms

3.3.2. Regulation

Institutional pressures include regulation as a coercive force (DiMaggio & Powell, 1983). AI involves handling large amounts of confidential data, creating legal risks that prompt strict regulations. Data use requires stakeholder consent (Merhi & Harfouche, 2023), and organizations remain legally liable for AI decisions (Krausová, 2017), which can make adopting responsible AI challenging (Cath, 2018).

In Europe, the AI Act classifies AI by risk level and mandates human oversight, transparency, security, non-discrimination, and traceability (Solomon & Davis, 2023). Compliance with GDPR adds further challenges, including anonymization of personal data and protection of employees from AI surveillance (Pumplun et al., 2019). As for Morocco, the law remains ambiguous regarding the use of AI. However, despite the absence of laws specifically addressing the use of AI to date, the country has established general regulations concerning the security of personal data and electronic transactions. Examples include Law 09-08 on the protection of individuals with regard to the processing of personal data, Law 07-03 on intrusions into automated data processing systems, and Law 05-20 on cybersecurity (Adnani & Haounani, 2024).

Studies by Merhi & Harfouche (2023), Nam et al. (2021) and Pumplun et al. (2019) examined the impact of legal requirements on AI implementation in organizations. In audit firms, Simina & Dutescu (2024), Seethamraju & Hecimovic (2023) and Yang et al. (2024) highlighted challenges in documenting auditors' AI use and the lag of audit standards behind innovations. Thus, the following hypothesis is proposed:

H8: Regulation has a negative impact on the adoption of AI in audit firms

3.3.3. Professional bodies support (OEC)

In Morocco, statutory audit is regulated by Law 15-89, which established the Order of Certified Public Accountants (OEC) to uphold ethics and protect the profession. Membership in professional organizations, such as the OEC, creates normative pressure by defining auditors' standards and fostering professional recognition, leading firms to align with network norms (DiMaggio & Powell, 1983).

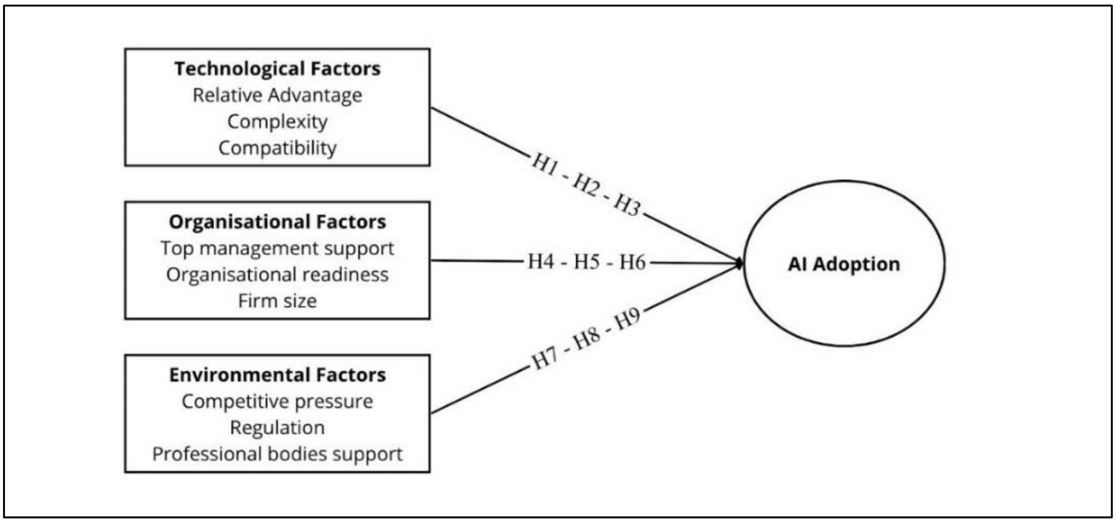
Support from professional organizations encourages audit firms to adopt new technologies (Rosli et al., 2016). Professional associations enhance adoption by raising awareness of innovations, highlighting professional development, and providing practical support, particularly for small firms (Swan & Newell, 1995). Knowledge-sharing communities further support professionals in implementing technologies like AI (Jackson & Allen, 2024).

The positive influence of professional associations on technology adoption within companies has been examined in studies such as those by Rosli et al. (2016), Rosli et al. (2013), Swan & Newell (1995) and Jackson & Allen (2024). We therefore propose the following hypothesis:

H9: The OEC's support has a positive impact on the adoption of AI in audit firms

The following figure summarizes our conceptual research model:

Figure N°2: Research model



Source: Authors

Discussion

This research contributes to understanding AI adoption in audit firms by combining the TOE, DOI, and institutional theory frameworks. Considering technological, organizational, and environmental factors provides a comprehensive view of adoption determinants. Technological traits, such as relative advantage, complexity, and compatibility, shape perceptions of AI's usefulness. Organizational factors, including top management support, readiness, and firm size, drive successful implementation. Environmental factors, such as competitive pressure, regulation, and professional organization support, reflect external influences. This multidimensional approach goes beyond user- or technology-focused models, showing how internal and external conditions jointly shape AI adoption.

To validate this model, data should be collected from various audit firms, from the Big Four to smaller independent firms. Surveys can measure technological, organizational, and environmental factors, while analyses such as structural equation modeling (SEM), can test relationships and identify key drivers. Adding qualitative interviews would clarify adoption obstacles and internal mechanisms, particularly where resources and readiness differ. Comparing firms of different sizes could also reveal moderating effects, like the influence of firm size or prior experience.

The expected results could guide AI integration in audit firms by highlighting key technological and organizational levers, strengthening management support, and improving readiness. Awareness of institutional and regulatory pressures would help firms remain competitive. Thus, the framework offers both a theoretical contribution and practical guidance for the audit sector.

Conclusion

The integration of ICT in organizations is rooted in theories explaining the intention to adopt technology. At the individual level, models like TRA, TPB, TAM, and UTAUT examine adoption based on psychological factors. However, organizational adoption requires broader frameworks, such as DOI and TOE, which consider organizational and environmental dimensions critical for predicting ICT adoption.

Our study adopted an organizational perspective, using the TOE framework, DOI, and institutional theory to examine key determinants. Technological characteristics significantly influence adoption decisions, with organizations favoring technologies offering greater benefits and performance. Accordingly, we focused on the three most studied DOI variables: relative advantage, complexity, and compatibility.

However, an organization's internal processes, culture, and structure play a key role in the speed at which AI is adopted. The TOE framework posits that current business practices and the way information flows among employees can facilitate the dissemination and transfer of any technological innovation. Thus, we determined that management support, organizational readiness, and the size of the organization are the most influential organizational variables to examine in our conceptual model.

Finally, decisions regarding technological innovation do not stem solely from internal corporate policies. External forces, which are part of the entity's environment, influence these decisions and drive organizations to adopt AI for faster decision-making. Environmental context draws on institutional theory, which posits that organizations' choices are not free. Their decisions are influenced by pressures from external stakeholders—namely competitors, regulators, and professional associations—which they are required to comply with.

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