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The adoption of artificial intelligence in internal audit: determinants, uses and challenges – a systematic review of the literature based on Prisma

Nadia TOUTOUH¹, Houda BENARBI²

¹PhD student at ENCG El Jadida, Chouaib Doukkali University, Morocco, toutouh.n@ucd.ac.ma

²Research professor at ENCG El Jadida, Chouaib Doukkali University, Morocco, benarbi.h@ucd.ac.ma

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ABSTRACT

The integration of artificial intelligence into internal audit is progressing rapidly, driven by developments in machine learning, predictive analytics, natural language processing and, more recently, generative artificial intelligence. This study aims to systematically analyse the determinants of AI adoption in internal audit; its main uses and the challenges

associated with its integration. A systematic literature review was conducted in accordance with the PRISMA 2020 guidelines, using the Scopus and Web of Science databases, covering the period 2015–2026. Following identification, deduplication, screening and eligibility assessment, 35 studies were selected for analysis. The results show that the adoption of AI depends primarily on technological maturity, data quality, auditors' skills, organisational support, governance and trust in the systems. Its main applications relate to risk

assessment, anomaly detection, task automation, continuous auditing, document analysis and decision support. The main challenges relate to governance, explainability, reliability, skills, human oversight and data protection. The review highlights the multidimensional nature of AI adoption and emphasises the importance of aligning technologies, human capabilities and governance mechanisms to ensure controlled integration within the internal audit function.

Keywords: Artificial intelligence; Internal audit; Technology adoption; Generative artificial intelligence; Systematic review.

Introduction

Artificial intelligence is playing an increasingly significant role in the transformation of control, risk management and audit functions. The development of machine learning, natural language processing, predictive analytics and, more recently, generative artificial intelligence is changing the possibilities for data utilisation and the way in which organisations identify, analyse and monitor risks. In the field of internal audit, these technologies are gradually being deployed to process large volumes of data, detect anomalies, support risk assessment, automate certain repetitive tasks and strengthen the continuity of controls. Recent research also points to a broadening of applications to include literature reviews, text analysis, report preparation and support for professional judgement, particularly with the development of large language models and generative artificial intelligence tools (Emett et al., 2025; Wassie and Lakatos, 2024). AI is therefore moving beyond its status as an isolated technical tool to become progressively integrated into various phases of the internal audit process.

However, this development raises a key question regarding the conditions under which organisations and internal audit functions actually adopt these technologies. The mere availability of an artificial intelligence solution is not sufficient to explain its integration into professional practice. Several factors come into play in this process, notably the quality and accessibility of data, technological infrastructure, auditors' digital skills, management support, organisational maturity, trust in the systems, and the governance mechanisms governing their use. Research conducted in various contexts also shows that institutional conditions, available resources and user perceptions can influence how AI is accepted and integrated into the internal audit function (Gui et al., 2025; Jouiet and El Abbas El Ghaleb, 2025; Supapon and Pan-Ma-Rerng, 2024). At the same time, the use of these tools raises questions regarding the reliability of results, the explainability of models, data confidentiality, accountability for AI-assisted

decisions, and the maintenance of the auditor's professional judgement.

Despite the rapid increase in publications on this topic, the literature remains scattered across several perspectives. Some studies focus primarily on the factors that promote or hinder the adoption of AI, whilst others examine its applications in risk assessment, anomaly detection, cybersecurity, automation or continuous auditing. Another strand of research focuses more on skills, governance, trust, ethical issues or the risks associated with intelligent systems. Against a backdrop of the rapid spread of artificial intelligence technologies within internal audit functions, the literature therefore remains fragmented regarding the conditions for adoption, areas of application and the constraints associated with their integration. The aim of this review is therefore to understand how existing academic research frames the determinants, uses and challenges of adopting artificial intelligence in internal audit. Consequently, the central research question is as follows: how does the academic literature characterise the determinants, uses and challenges associated with the adoption of artificial intelligence in internal audit?

In this context, this article aims to systematically analyse the literature on the adoption of artificial intelligence in internal audit by structuring the review around three complementary dimensions: the determinants of its adoption, the uses developed in internal audit activities, and the challenges associated with its integration. To achieve this objective, a systematic review was conducted in accordance with the PRISMA 2020 guidelines, using the Scopus and Web of Science databases, covering the period 2015–2026 (Page et al., 2021). Following the identification, selection and eligibility assessment process, 35 studies were included in the analysis. The contribution of this research lies in linking the technological, human, organisational and institutional dimensions of AI adoption, whilst providing an overview of the main areas of application and the challenges associated with their development. This analysis helps to structure what is still a relatively new body of literature and provides a basis for identifying avenues likely to deepen our understanding of the integration of artificial intelligence into the internal audit function.

1. Conceptual and theoretical framework for the adoption of AI in internal audit

1.1. Artificial intelligence applied to internal audit

Artificial intelligence refers to a set of technologies capable of performing tasks that typically require human cognitive abilities, including learning from data, pattern recognition,

classification, prediction, natural language processing and content generation. In the field of internal audit, this concept encompasses several technological families whose applications are now complementary. Machine learning is used to identify patterns, detect anomalies and build predictive models from structured data, whilst natural language processing facilitates the analysis of documents, reports, internal policies and other textual sources. Neural networks and deep learning techniques are increasingly used in complex classification and detection tasks, whilst intelligent automation and RPA enable the execution of certain repetitive or standardised tasks. More recently, generative artificial intelligence and large language models have broadened the scope of application to include information retrieval, document summarisation, content preparation and support across the various phases of an audit engagement (Emett et al., 2025; Wassie and Lakatos, 2024).

The application of these technologies is gradually transforming the way in which auditors access information and conduct their analyses. Traditionally, certain audit procedures relied on the examination of samples or on processes carried out at specific points during the engagement. AI tools now facilitate the processing of larger volumes of data, the identification of atypical transactions, the continuous monitoring of certain processes and the prioritisation of areas presenting a higher level of risk. Their contribution is therefore not limited to the automation of existing operations, as they can also play a role in decision-making, the structuring of work and the interpretation of complex information. This development leads us to view AI as a component of the internal audit framework capable of supporting the effectiveness of the work and broadening analytical capabilities, whilst maintaining the need for validation and supervision by audit professionals.

1.2. The adoption of artificial intelligence in the internal audit function

The adoption of artificial intelligence in internal audit is not merely a matter of acquiring or using a tool on an ad hoc basis. It refers to a process through which an organisation gradually integrates AI technologies into the practices, working methods and control mechanisms of the internal audit function. This adoption can take several forms, ranging from experimentation on a limited number of cases to regular use across several stages of the audit process. The extent of adoption depends, in particular, on the availability of data, the organisation's technological maturity, the skills of the auditors, managerial support and the existence of rules governing the use of intelligent systems. Recent research also shows that users' acceptance of the technology, their trust in

the results produced and their perception of its usefulness are important aspects of the adoption process (Gui et al., 2025; Supapon and Pan-Ma-Rerng, 2026).

In the context of internal audit, this adoption must also be distinguished from mere automation. AI can support operational tasks, but it can also be used in risk analysis, anomaly detection, continuous monitoring, documentary research or decision support. Its integration therefore becomes more profound when it is embedded within the organisation's audit routines, information systems and governance mechanisms. The literature highlights a shift from predominantly technical use towards a more structured adoption, in which human, organisational and institutional considerations are playing an increasingly significant role. The adoption of AI in internal audit can therefore be regarded as a multidimensional process combining technology, skills, organisation and governance.

1.3. Key theoretical approaches used to explain the adoption of AI

The literature on the adoption of artificial intelligence in internal audit draws on several complementary theoretical frameworks. The Technology Acceptance Model (TAM) is notably used to analyse the role of perceived usefulness, ease of use, attitude towards technology and trust in the intention to adopt AI tools (Davis, 1989). This approach is particularly well-suited when the analysis focuses on auditors' individual perceptions and their willingness to integrate new technologies into their professional practices. Other studies draw on the TOE framework, which simultaneously considers the technological, organisational and environmental dimensions of adoption (Tornatzky and Fleischer, 1990). From this perspective, the integration of AI depends not only on the technical characteristics of the available solutions, the organisation's internal resources and capabilities, and managerial support, but also on the regulatory and institutional context in which the audit function operates.

Some research also adopts an approach based on organisational resources and capabilities, viewing digital skills, data, infrastructure and analytical capabilities as strategic resources necessary for the integration of AI (Barney, 1991). This perspective emphasises the organisation's ability to combine its technological and human resources to create value from intelligent tools. In the specific field of internal audit, these theoretical approaches converge on a single idea: the adoption of AI results from a set of interdependent factors and cannot be explained solely by the technical characteristics of the tools. User behaviour, available resources, organisational maturity, governance and

the institutional environment must be considered jointly to understand the conditions for the sustainable integration of artificial intelligence into the internal audit function.

2. PRISMA-compliant systematic review methodology

2.1. Determinants of the adoption of artificial intelligence in internal audit

The literature identifies the adoption of artificial intelligence in internal audit as the result of several complementary conditions. From a technological perspective, the availability of suitable infrastructure, the quality of information systems, and the accessibility and reliability of data are important prerequisites, as the performance of AI solutions depends directly on the data used and its integration into the organisation's digital environment. Added to this are human factors, notably auditors' digital and analytical skills, their understanding of the technologies used, and their ability to interpret the results produced by the models. Perceived usefulness, ease of use and trust in the systems also influence the acceptance of these tools and their integration into professional practices (Gui et al., 2025). Adoption therefore appears more likely when users possess both the necessary skills and a positive perception of AI's contribution to their activities.

The organisational dimension also plays a central role. Support from senior management, the availability of resources, digital maturity and the existence of a clear technology integration strategy can facilitate the transition from one-off trials to regular use within the internal audit function. At the same time, research highlights the importance of AI governance, particularly the definition of responsibilities, rules of use, data protection and mechanisms for supervising automated systems. In certain contexts, regulatory and institutional requirements also influence adoption decisions, particularly when AI is applied to sensitive activities relating to control, risk or compliance. The work of Jouiet and El Abbas El Ghaleb (2025), particularly in the Moroccan context, highlights the interaction between technological, organisational and environmental dimensions, whilst Supapon and Pan-Ma-Rerng (2026) emphasise the role of organisational readiness and managerial support. Taken together, these contributions lead us to view the adoption of AI as a process that depends on a combination of technological, human and organisational capabilities, rather than solely on the availability of a technical solution.

2.2. Uses of artificial intelligence in internal audit

The literature highlights a gradual diversification in the uses of artificial intelligence across the various phases of the internal audit process. The most frequently studied applications relate to risk assessment, the detection of anomalies and the automation of certain operations. Machine learning and predictive analytics techniques are used, in particular, to identify unusual patterns, detect atypical transactions and direct audit work towards areas presenting a higher level of risk. These tools can also contribute to more continuous monitoring of activities by analysing larger volumes of data than those generally covered by traditional methods. Several studies show that AI is used to improve the targeting of controls, enhance the early detection of irregularities and support risk prioritisation in engagement planning (Herrerros-Martínez et al., 2024; Duhova et al., 2026).

Other applications include intelligent automation, document analysis and assistance with cognitive tasks. RPA and intelligent systems can be deployed to carry out repetitive tasks, process standardised data or facilitate certain routine audits. Automatic natural language processing and large language models are now extending these possibilities to include document analysis, information retrieval, content summarisation, report preparation and assistance in drawing conclusions. Generative artificial intelligence is thus introducing new applications within the internal audit function, taking on activities that previously required greater human intervention, whilst maintaining the need for professional validation of the results produced (Emett et al., 2025; Aljabri and Alnajim, 2026). The literature therefore indicates a gradual shift from applications primarily focused on automation and data analysis towards more integrated uses, covering the planning, execution, documentation, reporting and follow-up of audit engagements.

2.3. Challenges associated with the integration of artificial intelligence into internal audit

The literature highlights that the integration of artificial intelligence into internal audit is accompanied by several challenges that go beyond the purely technical dimension. Issues of governance, accountability, regulation and ethics are of significant importance, particularly when AI systems are involved in risk analysis, the detection of anomalies or the generation of evidence that may influence the auditor's conclusions. Several studies also emphasise the importance of the explainability and reliability of the results produced by the models, given that professionals must be able to understand, verify and justify the results used in their work (Anomah et

al., 2026; Osman, 2026; Hu et al., 2023). Added to these challenges are issues of data protection, confidentiality, cybersecurity and compliance, which become particularly sensitive when AI systems utilise internal, financial or strategic data. Recent developments in generative artificial intelligence have heightened some of these concerns, particularly due to the risk of inaccurate responses, content that is insufficiently traceable or results that are difficult to explain, which justifies the continued use of human validation of the generated output (Emett et al., 2025; Aljabri and Alnajim, 2026).

The challenges also relate to skills and the organisation of work. Several studies highlight the need to strengthen auditors' digital, analytical and technological skills so that they can use AI tools appropriately, interpret their results and identify their limitations (Wassie and Lakatos, 2024; Aldemir and Uçma Uysal, 2024). A lack of training, insufficient resources or excessive reliance on automated systems can reduce the quality of their integration and increase the risk of uncritical use of the results generated. At an organisational level, technological maturity, the quality of infrastructure, data availability, integration costs and management support are also challenges regularly highlighted in the literature, particularly in contexts where digital capabilities remain unevenly developed (Jouiet and El Abbas El Ghaleb, 2025; Ghazi, 2024). Overall, the research converges on the idea that AI should be integrated as a tool to support professional judgement rather than as a substitute for the auditor, which requires maintaining clearly defined responsibilities, oversight mechanisms and sufficient control over the risks associated with its use.

3. Methodology of the systematic review according to PRISMA

3.1. General approach and protocol for the systematic review

This study is based on a systematic literature review conducted in accordance with the PRISMA 2020 guidelines, the aim of which is to ensure transparency in the process of identifying, selecting, assessing eligibility and including studies (Page et al., 2021). The protocol was defined prior to the analysis of the corpus in order to minimise selection bias and maintain consistency between the research question, the eligibility criteria and the synthesis strategy. The review aims to identify the main determinants of the adoption of artificial intelligence in internal audit, to characterise its uses and to highlight the challenges associated with its integration. The search was conducted in Scopus and the Web of Science Core Collection, covering the period 2015–2026, and included

publications in English and French, as well as articles and journal articles. The search strategy combined terms relating to artificial intelligence, such as 'artificial intelligence', 'machine learning', 'deep learning', 'generative AI' and 'natural language processing', with expressions directly linked to internal audit, notably 'internal audit', 'internal auditing' and 'internal audit function'. The concepts of determinants, uses and challenges were not included as mandatory filters in the main search criteria so as not to exclude relevant works using different formulations; they were applied during the data extraction and thematic coding stages.

The search initially identified 221 references in Scopus and 72 in Web of Science. After applying the criteria relating to time period, language and document type, 147 references were retained, comprising 92 from Scopus and 55 from Web of Science. The removal of 41 duplicates resulted in 106 unique references, which were then screened on the basis of their title and abstract. Fifty-nine publications were excluded at this stage, mainly because their scope was too broad for internal audit, AI played only a marginal role, or their focus centred on other forms of audit. Forty-seven studies underwent in-depth scrutiny, of which twelve were excluded, resulting in a final corpus of 35 publications. For each selected study, a data extraction grid was used to identify methodological characteristics, context, technologies employed, adoption factors, areas of application, identified constraints and key findings. The synthesis is then based on a cross-cutting thematic coding approach, adapted to the heterogeneity of the methodological approaches and the fields studied, in accordance with the principles of narrative synthesis recommended in systematic reviews when statistical meta-analysis is not appropriate (Page et al., 2021).

3.2. Literature sources and search strategy

The literature search was conducted in Scopus and Web of Science Core Collection, selected for their coverage of research in auditing, management, information systems and artificial intelligence. The period under consideration spans from 2015 to 2026, with the selection limited to journal articles published in English or French. The search strategy combined terms relating to artificial intelligence, such as 'artificial intelligence', 'machine learning', 'deep learning', 'generative AI' and 'natural language processing', with expressions linked to internal audit, notably 'internal audit', 'internal auditing' and 'internal audit function'. This combination was intended to maintain a sufficiently broad scope to identify relevant work without prematurely restricting the search to the terms 'adoption', 'uses' or 'challenges' alone (Page et al., 2021).

3.3. Search queries and eligibility criteria

The search queries were adapted to the specific syntax of each database whilst retaining the same conceptual structure. They combined terms relating to artificial intelligence with those explicitly referring to internal audit, with the search conducted across titles, abstracts and keywords. Studies were included where they dealt substantially with artificial intelligence in the context of internal audit and provided insights into its adoption, uses or challenges. Excluded were studies focusing exclusively on external audit, digital technologies without a clearly identifiable AI component, publications outside the specified time period or languages, and documents that did not correspond to the selected publication types. The criteria were applied consistently throughout the selection process to ensure the coherence of the corpus (Page et al., 2021).

3.4. Study selection process

The selection of publications followed the main steps of the PRISMA 2020 protocol, namely identification, deduplication, screening and eligibility (Page et al., 2021). After applying filters relating to the time period, language and document type, 147 references were retained, of which 92 were from Scopus and 55 from Web of Science. A comparison of titles and DOIs led to the identification of 41 duplicates, reducing the corpus to 106 unique references. An initial review of the titles and abstracts was then carried out to exclude publications not directly related to internal audit, those in which artificial intelligence played only a marginal role, and studies focusing on other forms of audit. This stage led to the exclusion of 59 references. The remaining 47 studies were subjected to a more in-depth assessment of their relevance to the research question and the three selected themes, namely the determinants, uses and challenges associated with the adoption of AI. At the end of this stage, a further 12 studies were excluded, resulting in a final corpus of 35 articles included in the systematic review.

Table1: Process for identifying and selecting studies according to PRISMA 2020.

PRISMA step	Description	Number
Identification	References selected in Scopus after applying filters	92
Identification	References selected in Web of Science after applying filters	55
Identification	Total references identified	147
Duplicate removal	Duplicates identified and removed	41
Screening	Unique references screened on the basis of title and abstract	106
Screening	References excluded following review of the title and abstract	59
Eligibility	Studies selected for in-depth review	47
Eligibility	Studies excluded following eligibility checks	12
Inclusion	Studies ultimately included in the systematic review	35

Methodological source: Page, M. J., et al. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ, 372, n71.

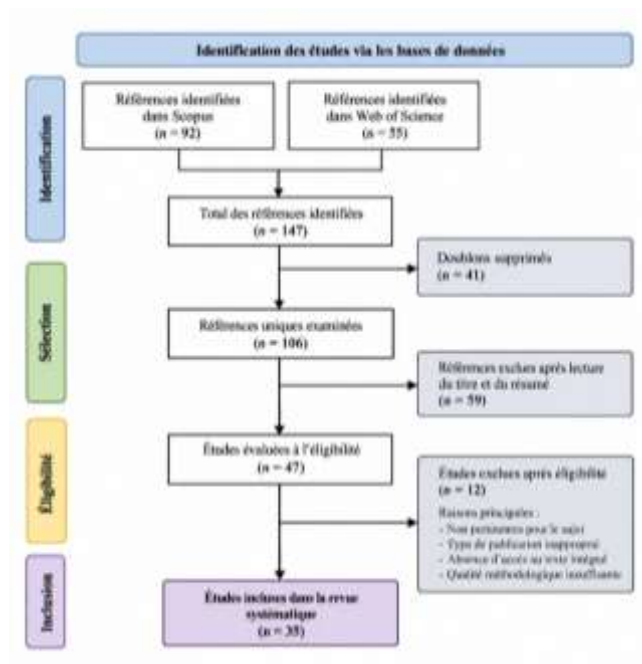


Figure1: PRISMA 2020 flow diagram of the study selection process.

Source: adapted from Page et al. (2021), PRISMA 2020.

3.5. Data extraction and coding

Data extraction was carried out using the 35 studies retained at the end of the selection process. A standardised data collection form was used to record, for each publication, the authors, year, geographical context, study type, methodology, sample or data used, the artificial intelligence technology studied, and the main findings. The information was then organised around the three central dimensions of the research: the determinants of adoption, the uses of AI in internal audit activities, and the challenges associated with its integration. A cross-cutting thematic coding approach enabled similar formulations to be grouped into homogeneous categories in order to facilitate comparison between studies and to identify the most recurrent themes in the corpus (Page et al., 2021).

3.6. Assessment of the methodological quality of the studies

The methodological quality of the 35 selected studies was subject to a specific assessment to verify the robustness of the corpus used in the synthesis. Given the heterogeneity of the research identified, a single assessment framework was not applied indiscriminately to all publications. Quantitative, qualitative, mixed-methods, experimental and conceptual studies, as well as reviews, were assessed using criteria tailored to their methodological nature, drawing primarily on the critical appraisal tools proposed by JBI (Aromataris et al.,

2024). The review focused on several common dimensions, notably the clarity of objectives, the description of the research setting and data, the consistency between the research question and the chosen method, the validity of the measures or sources used, the rigour of the analysis, the correspondence between the results presented and the data analysed, and the consideration of methodological limitations. For experimental studies or those falling within the scope of Design Science, particular attention was also paid to the description of the data, the model validation process and the reproducibility of the proposed approaches. This assessment was not used as a mechanical mechanism for ranking or exclusion, but as a means of evaluating the overall robustness of the knowledge incorporated into the review. The results show that the 35 studies satisfactorily meet the selected criteria and demonstrate a methodological standard compatible with their inclusion in the final synthesis. No further publications were therefore excluded at this stage, leaving the final corpus at 35 studies.

3.7. Methodology for synthesising and analysing the results

Given the diversity of methodological approaches, the fields of study and the artificial intelligence technologies employed, the results were not subjected to a statistical meta-analysis. A narrative and thematic synthesis was favoured in order to compare the contributions of the various studies whilst preserving their specific characteristics. The information extracted was first grouped according to the general characteristics of the corpus, notably, year of publication, geographical context, type of study, sector studied and AI technologies used. A second cross-cutting review was then conducted focusing on the three central dimensions of the review: the determinants of adoption, the uses of artificial intelligence in internal audit, and the challenges associated with its integration.

Related themes were grouped into common categories to highlight the dominant trends within the corpus. With regard to the determinants, the analysis focused in particular on skills, technological infrastructure, data quality, organisational support, governance and user perceptions. Uses were structured around the main audit activities concerned, such as risk assessment, anomaly detection, task automation, continuous auditing, planning and reporting. Challenges were examined from technological, human, organisational, regulatory and ethical perspectives. The frequencies associated with these categories were used for descriptive purposes, as a single article could contribute to several themes. The aim was therefore not to establish a hierarchy among the identified factors, but to highlight areas of convergence,

differences and areas that remain largely unexplored in the literature.

3.8. Methodological limitations of the review

Like any systematic review, this research is conducted within a defined methodological framework that must be clarified in order to contextualise the scope of the findings. The choice of Scopus and Web of Science is based on their recognised coverage of scientific publications in auditing, management, information systems and artificial intelligence, whilst prioritising high-quality academic sources. The period 2015–2026 was selected in order to focus the analysis on the recent phase of development and dissemination of artificial intelligence technologies in internal audit practices. The selection of publications in English and French also serves to ensure consistency in the analysis of the corpus. Furthermore, the diversity of geographical contexts, sectors and methodological approaches identified is a defining feature of the field under study; this justifies the use of a narrative and thematic synthesis rather than a uniform statistical comparison. Finally, the categorisation of studies according to determinants, uses and challenges was carried out using a structured framework and applied consistently across all the selected publications. These methodological choices define the scope of the review without undermining its ability to identify the main trends, areas of convergence in the literature and remaining avenues for research on the adoption of artificial intelligence in internal audit.

4. Results of the systematic review

4.1. General characteristics of the corpus

The final corpus comprises 35 studies published between 2021 and 2026, with a particularly marked concentration in the most recent years. Two publications date from 2021, one from 2022, one from 2023, nine from 2024, ten from 2025 and twelve from 2026. In total, 31 out of 35 studies were published between 2024 and 2026, highlighting the recent surge in research on artificial intelligence in the field of internal audit. This recent trend can be attributed in particular to the rapid advancement of predictive analytics, machine learning, natural language processing and, more recently, generative artificial intelligence and large language models. The geographical distribution also reveals a certain diversity in the contexts studied. Twenty studies have an international scope or are not linked to a single country, whilst the remaining studies mainly concern Saudi Arabia (four studies), Morocco (three), followed by Indonesia, Jordan and Türkiye (two studies each). Ghana and Oman are each represented by one study. This distribution shows that the issue of AI adoption in

internal audit is now being addressed across a range of institutional, economic and organisational settings, which helps to enrich our understanding of the phenomenon beyond any single national context.

Methodologically, the corpus presents a relatively balanced distribution across several types of research. Ten studies rely primarily on a quantitative empirical approach, ten employ experimental or Design Science methodologies, and ten consist of conceptual work or literature reviews. The remaining five studies are based on case studies, a qualitative approach, a mixed-methods approach or a specific methodological orientation. The sectors studied are also varied, with the majority of studies having a general or multi-sectoral scope, supplemented by research focusing on private and listed companies, the public sector, banking and financial institutions, higher education, industry and the energy sector. This diversity is also reflected in the artificial intelligence technologies analysed. Machine learning and predictive analytics tools feature prominently, alongside more general AI systems, natural language processing, generative artificial intelligence, robotic process automation and neural networks. Taken together, these characteristics demonstrate that recent literature on AI in internal audit has gradually diversified, both in terms of methodological approaches and in the fields of study and technologies employed, providing a sufficiently broad basis for subsequently analysing the main determinants of adoption, the observed uses and the challenges associated with its integration.

4.2. Determinants of the adoption of artificial intelligence in internal audit

The thematic analysis highlights several categories of factors that shape the adoption of artificial intelligence in internal audit activities. The most frequently identified determinants relate primarily to technological infrastructure, digital maturity and data quality, which were identified in 13 out of 35 studies, representing 37.1 per cent of the corpus. These elements form an essential foundation for the integration of AI solutions, insofar as their effectiveness depends heavily on the availability, reliability and accessibility of the data used by the audit function. Skills and human capital were next, appearing in 12 studies (34.3 per cent), which highlights the importance of internal auditors' technical and analytical capabilities in understanding, using and overseeing these new tools. Several studies highlight, in particular, the need to strengthen skills relating to data analysis, the interpretation of results produced by algorithms and the use of automated solutions in the audit process (Wassie and Lakatos, 2024; Aldemir and Uçma Uysal, 2024). The literature therefore shows that the adoption of AI does not rely solely on the availability of high-performance

technology, but also on the ability of the organisation and its professionals to integrate it into existing practices.

Organisational and institutional dimensions also feature prominently in the studies reviewed. AI governance, regulatory requirements and institutional pressures are mentioned in 9 studies, or 25.7 per cent, whilst management support and organisational readiness appear in 6 studies, or 17.1 per cent. These results show that adoption also depends on the existence of clear rules regarding the use of AI systems, accountability for decisions, data protection and the management of technological risks. Research conducted in various contexts also highlights the role of managerial support, organisational resources and alignment between AI tools and the objectives of the internal audit function (Supapon and Pan-Ma-Rerng, 2024; Jouiet and El Abbas El Ghaleb, 2025). In addition to these factors are user perceptions, notably trust, perceived usefulness and acceptance of the technology — s present in five studies, representing 14.3 per cent of the corpus — as well as costs, available resources and technical support, identified in four studies, representing 11.4 per cent. Some research shows that the intention to use AI is strengthened when auditors consider the tools to be useful, easy to integrate into their tasks and sufficiently reliable to support their professional judgement (Gui et al., 2025). Overall, the results show that the adoption of artificial intelligence in internal audit stems from the interaction between technological, human, organisational and institutional factors, rather than from any single isolated determinant.

4.3. Uses of artificial intelligence in internal audit activities

The studies analysed show that artificial intelligence is utilised at several stages of the internal audit process, with a particularly strong presence in activities relating to risk assessment, the detection of anomalies and the automation of processes. Risk assessment and prioritisation feature in 11 studies, representing 31.4 per cent of the corpus, making this the most frequently identified use. AI tools are used in particular to analyse large volumes of data, identify weak signals, prioritise areas of risk and direct work towards processes requiring special attention. The detection of anomalies, errors or fraud is mentioned in 8 studies, or 22.9 per cent, whilst 7 studies, or 20 per cent, focus on the automation of certain repetitive tasks and the associated efficiency gains. These uses relate in particular to data processing, the selection of transactions, the identification of atypical behaviour, or the performance of controls that can be partially automated. Research utilising machine learning, neural networks or anomaly detection methods illustrates this shift towards an audit approach based more on the continuous

use of data and an enhanced ability to rapidly identify unusual situations (Herrerros-Martínez et al., 2025; Duhova et al., 2026; Alotaibi et al., 2025).

Other applications relate more directly to changes in how audit engagements are conducted. Continuous auditing and automated monitoring are identified in 6 studies, or 17.1 per cent, as are applications related to cybersecurity, compliance and governance. The planning and targeting of engagements feature in four studies, whilst four papers also address report production, the communication of findings or assistance with drafting. Three studies highlight applications geared towards decision support and professional judgement, and three others towards documentary analysis, information search or the analysis of evidence. The recent emergence of solutions based on generative artificial intelligence and large language models has, in particular, expanded the scope of application to include document summarisation, knowledge base querying, report preparation and assistance to auditors during various phases of the engagement (Emett et al., 2025; Aljabri and Alnajim, 2026). Overall, the findings show that AI is no longer limited to being a one-off analytical tool: it is gradually being integrated into several internal audit activities, from planning and risk identification through to monitoring, documentation and the communication of findings.

4.4. Challenges associated with the integration of artificial intelligence into internal audit

Analysis of the corpus highlights several challenges associated with the integration of artificial intelligence into internal audit practices. Issues relating to governance, regulation, ethics and accountability are the most frequently cited, appearing in 12 studies, or 34.3 per cent of the corpus. These relate in particular to defining responsibilities for AI-assisted decisions, compliance with regulatory requirements, data protection and the oversight of the use of automated systems. Issues of explainability, the reliability of results and the risk of errors or ‘hallucinations’ are also prominent, featuring in 10 studies, or 28.6 per cent. These concerns take on particular significance when the tools are used in activities requiring a high degree of justification, such as risk assessment, the analysis of anomalies or the formulation of audit conclusions. Several studies highlight the need to maintain sufficient human oversight and to document the reasoning produced or supported by AI systems, particularly when these are involved in sensitive decisions or in the production of evidence.

Human and organisational challenges also feature repeatedly. A lack of skills or a need for training is highlighted in 9 studies (25.7 per cent), whilst 8 studies (22.9 per cent) emphasise the

importance of professional judgement, human supervision and the risk of over-reliance on automated tools. Difficulties relating to organisational integration and maturity in adoption are mentioned in 7 studies, as are technical limitations linked to the models or their performance. Issues concerning data quality, availability, confidentiality and security are identified in 6 studies (17.1 per cent), whilst costs, infrastructure and the necessary resources are mentioned in 5 studies (14.3 per cent). These results show that the main challenges do not relate solely to the technology itself, but to its ability to fit within a coherent control environment, with reliable data, appropriate skills, clearly defined responsibilities and oversight mechanisms proportionate to the intended uses. The integration of AI into internal audit therefore appears to be an organisational and professional process that requires a balance between technological performance, risk management and the preservation of the auditor's judgement.

4.5. Summary of the main findings of the review

An examination of the 35 studies highlights a gradual evolution of artificial intelligence, shifting from a tool primarily used to automate certain operations to a system integrated into several stages of the internal audit process. Recent research places significant emphasis on risk analysis, the detection of anomalies, the processing of large volumes of data and the development of more continuous forms of audit. The emergence of generative artificial intelligence is also broadening the scope of application to include document analysis, information retrieval, report preparation and support for professional judgement. However, this diversification of uses is accompanied by a shift in the conditions necessary for their adoption. Technological maturity and data availability remain important, but research is now paying increasing attention to auditors' skills, organisational support, governance mechanisms and trust in AI systems. Adoption therefore appears to be a multidimensional process in which technological resources must be aligned with human capabilities and organisational arrangements.

The findings also reveal that the benefits associated with AI are closely linked to the conditions under which the tools are designed, integrated and monitored. The potential for improving data coverage, risk detection and task automation is accompanied by requirements regarding model reliability, the explainability of results, data protection and the definition of responsibilities. The literature therefore tends to favour an approach based on complementarity between artificial intelligence and the auditor's expertise, rather than the replacement of professional judgement. This approach is particularly evident in research on generative AI and decision-support systems, where human oversight continues to be

regarded as an essential component of utilising the results produced by these technologies. Overall, the corpus therefore shows that the development of AI in internal audit depends less on the mere availability of tools than on organisations' ability to build a favourable environment combining infrastructure, data quality, skills, governance and control of the risks associated with their use.

5. General discussion and research agenda

5.1. General discussion of the results

The findings of this review confirm that the adoption of artificial intelligence in internal audit depends on a combination of technological, human and organisational factors. The predominance of factors relating to infrastructure, data quality and digital skills is consistent with research suggesting that the introduction of AI depends not only on the availability of technical solutions, but also on the organisation's ability to integrate them into its practices and to develop the skills required to utilise them. This interpretation is consistent with the resource-based view, according to which technologies create value only when combined with complementary internal resources, notably knowledge, skills and organisational capabilities (Barney, 1991). It also aligns with the findings of Wassie and Lakatos (2024), who emphasise the importance of skills, access to technological resources and organisational commitment in the evolution of the internal audit function, as well as those of Supapon and Pan-Ma-Rerng (2026), who highlight the influence of organisational readiness and socio-technical mechanisms on the adoption of AI. Similarly, the work of Gui et al. (2025) shows that perceived usefulness, ease of use and trust influence auditors' intention to integrate these technologies into their activities, bringing the observed results into line with the principles of Davis's (1989) technology acceptance model.

An analysis of current practices also shows that artificial intelligence is tending to play an increasingly significant role in the internal audit process. The most common applications remain linked to risk assessment, anomaly detection and the automation of certain tasks, which confirms the importance of analytical technologies in the recent evolution of the function. In particular, the work of Herreros-Martínez et al. (2025) illustrates the contribution of machine learning to the detection of anomalies within business processes, whilst Duhova et al. (2026) demonstrate how machine learning models can support risk management and internal audit practices. Alotaibi et al. (2024) also highlight the value of predictive approaches in enhancing the analysis and quality of the information utilised by the audit function. However, the

findings of the review indicate that applications are no longer limited to the quantitative analysis of data. The development of generative artificial intelligence is gradually expanding its applications to include literature research, information synthesis, report preparation and assistance for auditors. The study by Emmett et al. (2025), conducted in a real-world organisational context, illustrates this evolution by showing how ChatGPT can be integrated at various stages of the audit process, whilst Aljabri and Alnajim (2026) propose an approach based on retrieval-augmented generation to improve the relevance and traceability of responses used in an internal audit context. These findings reflect a gradual shift from a focus on automation towards one of cognitive assistance, in which AI acts more as a support for analysis and professional judgement.

This expansion of applications also explains the importance attached in the literature to issues of governance, reliability and oversight. The results show that explainability, accountability, data protection and the maintenance of human control become central considerations when AI is involved in activities likely to influence audit conclusions. Hu et al. (2023) highlight in particular the need to structure the governance of AI applications in audit activities, whilst Anomah et al. (2026) emphasise the importance of governance, trust and skills mechanisms in the use of AI for cybersecurity activities. In the banking context, Osman (2026) also demonstrates that the integration of AI into cybersecurity auditing requires a balance between technological performance and control mechanisms. The challenges identified by Jouiet and El Abbas El Ghaleb (2025) in the Moroccan public sector, particularly regarding infrastructure, skills, resources and the institutional environment, also serve as a reminder that adoption trajectories vary depending on the organisational context. These commonalities suggest that the maturity of AI adoption should not be assessed solely on the basis of the number of tools deployed, but also on the basis of the internal audit function's ability to oversee their use, to uphold the quality of professional judgement, and to integrate technological risks into its own governance mechanisms.

5.2. Research agenda

The findings of the review highlight several avenues for research that could expand current knowledge on the adoption of artificial intelligence in internal audit. A first area of focus concerns the study of the organisational mechanisms that determine the effective integration of these technologies. Future research could explore in greater depth the role of management support, digital maturity, data quality, auditors' skills and governance arrangements in the transition from the experimental use of AI to its sustainable integration into audit

processes. It would also be useful to distinguish more clearly between the different forms of AI employed, notably machine learning, natural language processing, intelligent automation and generative artificial intelligence, in order to determine whether their adoption drivers, benefits and constraints differ depending on their specific applications. Research would also benefit from a more detailed analysis of the effects of AI on the various phases of the audit engagement, from planning and risk assessment through to the formulation of recommendations and the monitoring of their implementation.

A second area of focus concerns the assessment of the effects of AI on the quality and performance of internal audit. A significant proportion of the current literature highlights potential benefits in terms of efficiency, data analysis and risk detection, but further empirical studies could measure these effects using comparable indicators and over longer periods. Longitudinal research would, in particular, enable us to observe how practices evolve following the introduction of AI solutions and to distinguish between immediate effects and more lasting transformations. The human dimensions also merit greater attention, notably the evolution of skills, the trust placed in systems, the interaction between the auditor and AI tools, and the conditions under which professional judgement can be enhanced rather than replaced. Finally, future research could give greater prominence to contexts that are still under-represented in the literature, particularly emerging economies, public sector organisations and certain highly regulated sectors. Comparisons across countries, sectors and levels of technological maturity would help to better understand the extent to which institutional and organisational conditions influence the trajectories of artificial intelligence adoption in internal audit.

Conclusion

The aim of this systematic literature review was to analyse the adoption of artificial intelligence in internal audit from three complementary perspectives: the determinants of its integration, its main uses and the challenges associated with its deployment. The analysis of the 35 selected studies, conducted using a structured approach inspired by PRISMA 2020, highlights a rapidly growing field of research, particularly since 2024. The results show that the adoption of AI relies on a set of interdependent factors, amongst which technological maturity, data quality and availability, auditors' skills, organisational support, governance and trust in the tools play a central role. At an operational level, artificial intelligence is being deployed in an increasingly diverse range of activities, ranging from risk assessment and the detection of anomalies to the automation of certain tasks, continuous auditing, document analysis, reporting and decision support.

The recent rise of generative artificial intelligence further expands these possibilities by introducing new forms of assistance in information processing and the production of content related to audit engagements.

The findings nevertheless emphasise that the integration of AI cannot be separated from the control mechanisms governing its use. Issues of reliability, explainability, data protection, accountability, skills and human oversight remain closely linked to the expected benefits of these technologies. One of the key lessons from this review therefore lies in the multidimensional nature of adoption: technological performance alone is not sufficient to guarantee the effective integration of AI into the internal audit function. This also depends on organisations' ability to develop the necessary skills, to structure their technology governance and to keep the auditor's professional judgement at the heart of the process. In this regard, the current literature opens up several avenues for more in-depth empirical research, particularly on the actual effects of AI on internal audit performance, on the forms of collaboration between auditors and intelligent systems, and on differences in adoption across institutional, sectoral and geographical contexts. This review thus helps to shape a field that is still evolving and offers an integrated understanding of the conditions, applications and challenges associated with the adoption of artificial intelligence in internal audit.

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