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Framework for Integrating Generative AI in Developing Competencies for Accounting and Audit Professionals

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Abstract: The study aims to identify the knowledge, skills and competencies required by accounting and auditing (AA) professionals in the context of integrating disruptive Generative Artificial Intelligence (GenAI) technologies and to develop a framework for integrating GenAI capabilities into organisational systems, harnessing its potential to revolutionise lifelong learning and skills development and to assist day-to-day operations and decision-making. Through a systematic literature review, 103 papers were analysed, to outline, in the current business ecosystem, the competencies' demand generated by AI adoption and, in particular, GenAI and its associated risks, thus contributing to the body of knowledge in underexplored research areas. Positioned at the confluence of accounting, auditing and GenAI, the paper introduces a meaningful overview of knowledge in the areas of effective data analysis, interpretation of findings, risk awareness and risk management. It emphasizes and reshapes the role of required skills for accounting and auditing professionals in discovering the true potential of GenAI and adopting it accordingly. The study introduces a new LLM-based system model that can enhance its GenAI capabilities through collaboration with similar systems and provides an explanatory scenario to illustrate its applicability in the accounting and audit area.

Keywords: Generative Artificial Intelligence (GenAI); competencies; accounting and auditing (AA); GenAI risks; Large Language Model (LLM)

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1. Introduction

The rapid development and disruptive progress in Artificial Intelligence (AI), which is dramatically transforming many aspects of employees' personal and professional lives, is raising questions in academia and business about the new skills needed by accounting and auditing (AA) professionals [1–3] as they integrate AI solutions into their day-to-day work [4–6]. Recent studies have pointed out that Big4 firms report significantly higher expertise in using AI than other AA companies [7,8], hence the role of these technologies in creating critical competitive advantages in the current context [9]. Statistical figures reinforce this idea, with AI in the accounting services market being estimated at USD 1.56 billion in 2024 and expected to reach USD 6.62 billion by 2029, with a compound annual growth rate (CAGR) of 33.5% for the forecast period 2024–2029 [10].

A new entrant in the AI technologies group, Generative Artificial Intelligence (GenAI), holds significant potential to transform the field of accounting and auditing, with the academic and business communities investigating its applicability in the AA sphere [5]. Accountants and auditors who can combine knowledge, skills and competencies required by the profession with those using GenAI products will benefit from the opportunity to increase the efficiency and accuracy of their work results [11]. Studies on the adoption of innovative technologies, including AI, in accounting and auditing have focused on topics of interest, such as the impact on the profession [12–14], changes in learning programs and the need for advanced skills of accountants and financial auditors [4,15] or the assessment of AI acceptance in accounting [16]. Researchers have highlighted the correlation between the use of emerging technologies in these areas and the skills development of AA professionals. Considering that GenAI will impact the way humans assimilate and process information and knowledge [17,18], the skills needed by accountants in the coming years should encompass both technical and social abilities [19].

Large consulting firms in the accounting and auditing industry are showing increased interest in integrating AI technologies [7,20], and recent research has pointed to significant progress in their use in most business processes in organizations [21,22]. To our knowledge, there are no studies that have addressed both the leveraging of GenAI in accounting and auditing and the emergence of new competency requirements for AA professionals in relation to integrating GenAI into their activities. In attempting to contribute to filling the existing gaps in the specialised literature, in this work, we aimed to address the following research questions:

RQ1. What knowledge, skills and competencies are needed by accounting and auditing professionals to effectively harness Generative Artificial Intelligence, and what are the risks of using it in this area?

RQ2. How can organisations integrate Generative Artificial Intelligence capabilities into information systems to develop the competencies of accounting and audit professionals?

We consider that GenAI can demonstrate its effectiveness in accounting and auditing when its users have both the competencies to manage it and the advanced analytical skills to interpret the results generated, using critical thinking to filter and evaluate them to make informed decisions. Therefore, this study starts from the premise that the widespread AI solutions and GenAI adoption in the AA domain generate the need to encourage and direct human resources towards improving and enriching skills. This premise aligns with the vision of international bodies that promote close cooperation between governments and stakeholders so that people are equipped with the necessary competencies that enable them to use and interact effectively with AI systems [23].

The main objectives of this study are (1) to identify the competencies, skills and knowledge required by accounting and auditing professionals to operate AI/GenAI systems effectively and (2) to provide a framework that can be used to integrate LLM-based GenAI systems into AA domain.

Considering the revealed aspects, the research is structured as follows: the first section presents the results of the literature review; the second describes the applied research methodology; the third includes the research results, picturing the framework for integrating Generative Artificial Intelligence in the development of accounting and auditing professionals' competencies; and the fourth focuses on discussions and research limitations. Conclusions, contributions, implications and future research directions of the research are drawn at the end of the article.

2. Literature Review

2.1. Generative Artificial Intelligence

Although the term "artificial intelligence" was first introduced in 1956 as part of the Dartmouth Summer Research Project on Artificial Intelligence by John McCarthy, Marvin Minsky, Nathaniel Rochester and Claude Shannon, there is arguably a consensus on the current importance of Artificial Intelligence systems with learning, reasoning and adaptive capabilities [24].

A subset of AI is Generative Artificial Intelligence, defined as a technology that provides human-like responses in the form of text, images and video content using Deep Learning (DL) and Natural Language Processing (NLP) models [25], following the requests formulation [26]. Unlike traditional AI systems, which use predefined datasets and rule-based programming [27], GenAI can generate novel, original content to provide answers to complex and diverse queries [28]. The launch of OpenAI's ChatGPT chatbot has paved the way for significant progress in AI. The integration of DL and language models based on the Generative Pre-Training Transformer (GPT) architecture significantly expands the capabilities of these programs [29], which replicates the activity of the human brain in the process of learning and developing the responses provided for the requests sent [30].

Large Language Models (LLMs) represent a particular type of GenAI trained on large datasets using advanced DL techniques to analyse and understand patterns and structures, creating the prerequisites for generating similar items [18,31,32]. LLMs serve as a "base model" and provide a starting point for the development of more advanced and complex models [27,33,34]. LLM models are increasingly used in content generation, information retrieval in unstructured data, data conversions, data organisation or detailed data analysis, addressing diverse business needs.

For the use of LLM-based systems, two techniques are known and harnessed in practice: fine-tuning and prompt engineering [35,36]. Fine-tuning is the technique by which a pre-trained model is adapted to a particular domain by training it further on a task-focused dataset. It involves improving the model by learning from the specified dataset. Prompting, on the other hand, is considered a more straightforward technique that does not involve modifying the model but only adjusting the way it is queried to guide it in the right direction [37]. The prompt can be a word, a sentence or phrase, a list of instructions or possible input data that has the effect of generating a relevant response in the context created [38]. Various strategies regarding the prompting technique of LLM-based systems are highlighted in research studies and used in practice: Zero-Shot—prompting a task in a way that LLM can understand and generate an appropriate response without explicit input, Role-Playing—simulating a profession-specific role along with the formulation of the prompt to solve the task for greater contextualization [39] and Chain-of-Thoughts (CoT) prompting—requesting to solve a task accompanied by prompting on providing the reasoning steps [40,41]. Masikisiki et al. [42] illustrated the use of the CoT technique as a method to train LLM-based system users to efficiently train models to obtain more relevant results. From another perspective, CoT can bring the benefit of understanding the reasoning of solving a complex problem by the LLM-based system user, thus contributing to the skills or knowledge development in the domain they are interested in.

Floridi [43] presented the concept of AI2AI, which involves the ability of LLM-based systems to collaborate and form connections with other similar systems, thus enabling interoperability for more relevant responses. On the other hand, LLM-based systems can generate plausible answers that may sometimes be incorrect, a phenomenon known as AI Hallucination, due to the biased (incomplete or incorrect) data sources on which LLMs are modelled/trained. To manage this problem, one solution that has proven viable is to combine the capabilities of LLM-based systems with external sources [44]. LLM-based GenAI systems have revolutionary potential, which can become disruptive through significant impact on society and organisations [32].

2.2. New Competencies Requirements for Accounting Professionals and Auditors in the AI-Integrating Context

2.2.1. Insights from the Academic Literature

The competencies of an organization's staff are crucial, often serving as a key factor for competitive advantage [45]. From a management theory perspective, one of the pioneers of competency research is David McClelland, who described competency as "a symbol for an alternative approach to traditional tests of in-smartness" [46]. A landmark is the definition of competence as a characteristic of a person, which can be a trait, a skill, an aspect of self-image or social role, or a set of knowledge that a person uses [47].

Recently, a government initiative [48] has defined AI Skills for Business, grouped into four categories—cognitive, functional, personal/behavioural and ethical—to support organisations in developing strategies to upskill staff using AI solutions in their daily work. In accounting and auditing, various studies have highlighted the correlation between professionals' competencies and the extent to which they use innovative technologies in their activities. Andreassen [49] mapped current skills of accountants and identified new ones, such as (i) statistical knowledge for preparing data or interpreting predictive models; (ii) performance analysis and client segmentation; (iii) monitoring IT system integrations and electronic exchange of accounting data between systems. Hence, the key role of AA professionals is to adopt and exploit the benefits of these technologies. Arguing the need to reshape skills of the accounting professionals, [50] discussed courses integrating elements of AI and RPA, taught at a US public university.

As the accountant's tasks and expertise are taken over by technology, the accountant's remit becomes narrower and more specialised, with the evolution of the accounting profession necessitating a scope expansion of technical skills [51]. The emergence of inter-professional competencies has led accountants to move towards other roles close to their identity, which, until recently, did not fit into their specific duties. It is also becoming imperative for auditors to acquire new technical skills for obtaining and interpreting financial audit results using modern technologies [52] and to focus on innovative supporting tools that imply the assumption of a continuous learning process [53]. Mathisen and Nerland [54] confirmed that newly adopted technologies play a crucial role in financial auditing by raising awareness, mobilizing for learning at work, facilitating learning and developing auditors' competencies. Mancini et al. [55] assessed smart technologies and mapped the set of Knowledge, Skills, Abilities (KSAs) required to manage decision-supporting information by leveraging AI, Big Data and Blockchain. Noordin et al. [56] explored external auditors' perception of using Artificial Intelligence (AI) and its contribution to audit quality. The study highlighted the significance of engaging skilled accounting and auditing professionals to incorporate AI into audit tasks, thereby minimizing the related risks. Consequently, auditors should enhance their technical capabilities, irrespective of the type of audit firm they are employed by. Similarly, in a study aimed at assessing individual factors that may contribute to the effectiveness of fraud risk assessment among external auditors, Ridzuan et al. [57] evaluated the crucial role of digital technology skills in enhancing this ability.

Among profession-specific skills in financial auditing, critical thinking is considered essential when using IT technologies. It is important to interpret the results obtained using AI through the lens of professional reasoning. Sceptical thinking and mental representations, which can be fostered by training skills in the sphere of 'problem solving', are also valued [58,59].

Although emerging technologies appear to have improved the efficiency and effectiveness of audit work [60], there is the risk that some professional skills be diminished due to the use of AI technologies in specific activities [61]. Over-reliance on AI could lead auditors to neglect professional judgement, resulting in the risk of missing findings, misdiagnosing and misinterpreting data identified by AI.

Possessing technical skills is a sine qua non in the GenAI adoption and associated risk management [62,63]. Their perishable nature leads organisations to generally prefer human resources that primarily possess soft skills: communication, flexibility, teamwork, personal branding, proactive problem-oriented thinking, motivation and confidence [64,65]. Unlike technical skills, social skills are more closely related to personal characteristics and are more difficult to obtain or develop over time.

2.2.2. Professional Accounting Bodies Perspective

The first professional accounting bodies (PABs) were established in the second half of the 19th century in the United Kingdom and obtained Royal Charter status, which implies they are given the right to regulate their activities and decide the process and criteria for membership [66,67].

Today, most national and international professional accountancy bodies are part of the International Federation of Accountants (IFAC), which comprises more than 180 professional accountancy organizations in more than 135 jurisdictions, representing millions of professional accountants [68]. Professional accounting bodies exert significant influence on accounting and business activity and play a crucial role in shaping professional direction, being considered the profession's principal guardians [69].

At the same time, tertiary accounting education relies on the accreditation of professional accounting bodies to certify that their graduates have developed the skills, knowledge and competencies needed to enter the accountancy profession [67]. On the other hand, the close and deep relationship of PABs with universities and higher education has some difficulties due to the increasing number of accounting professional interns employed directly by school [66].

For the analysis of the competencies recommended by professional regulatory and standard-setting bodies, three global and three nationally recognised organisations with significant influence on AA and accounting professionals were selected [69]. The Association of Chartered Certified Accountants (ACCA), with over 500,000 members and students; the Chartered Institute of Management Accountants (CIMA), with over 650,000 members and students; and the Institute of Management Accountants (IMA), with over 140,000 members, are international professional bodies that work continuously with industry experts and employers to ensure consistency between their requirements and recommended competencies. The American Institute of Certified Public Accountants (AICPA), established in 1887, having nowadays over 430,000 members; the Institute of Chartered Accountants in England and Wales (ICAEW), established in 1880; and the first PAB, established in 1854, the Institute of Chartered Accountants of Scotland (ICAS), are national professional bodies whose recommendations are based on extensive research, consultation with industry experts and analysis of evolving regulatory and market requirements. CIMA and AICPA have jointly developed the Chartered Global Management Accountant (CGMA) accreditation.

A synoptic table of the main classes of competencies considered by each professional body was drawn up in Table 1.

Table 1. Synopsis of core competencies.

Professional Body	Classes of Competencies
ICAEW (2018)	Ethics and professionalism; communication; teamwork; decision-making; problem-solving; adding value; technical competence [70]
ACCA (2020)	Ethics and professionalism; data, digital and technology; strategy and innovation; leadership and management; stakeholder relationship management; governance, risk and control; corporate and business reporting; financial management; management accounting; taxation; audit and assurance; advisory and consultancy [71]
AICPA & CIMA (2022)	Technical skills; business skills; people skills; leadership skills; digital skills [72]
ICAS (2023)	Ethics and integrity; communications; teamwork and leadership; personal effectiveness; problem-solving and decision-making; technical competence [73]
IMA (2023)	Strategy, planning and performance; reporting and control; business acumen and operations; technology and analytics; leadership; professional ethics and values [74]

Following the analysis of the competency's classes recorded in the consulted documents, it was observed that competencies from the field of integrated technologies were explicitly included in the AA area: "Technical competence"—ICAEW, AICPA and ICAS, "Data, Digital and Technology"—ACCA, "Digital skills"—AICPA, "Technology and Analytics"—IMA. Moreover, as the year of document publication is more recent, two classes of skills in the digital area in the same framework have even been identified (AICPA, 2022: "Technical skills" and "Digital skills") [72]. All these align with the academic literature review insights. Reviewing the considerations on newly emerging requirements for accountants' and auditors' competencies generated by the integration of AI/GenAI/LLM solutions, it was found that there are no clear formulations regarding them in the specialized literature. Therefore, the positioning of the present research in this area aims to fill existing gaps, enriching the body of knowledge in the investigated field and providing benchmarks for addressing and shaping the development and learning plans of AA professionals at the organisational level.

2.3. Risks of Using AI in the Accounting and Auditing Professions

With the relatively recent emergence of GenAI technologies, its use in accounting and auditing exposes organisations [75] to specific risks.

The risk of maladjustment revealed in the literature arises because of accountants' and auditors' non-compliance with the requirements of using new IT [76,77]. Burns and Igou [76] noted that, under AI exploitation, users are often forced to adapt to intrusive interfaces, which can be perceived as a threat to privacy by violating certain social norms or boundaries. In these situations, flexibility, proactive thinking and adaptability are essential.

Tasks and competencies for accounting professions will undertake major changes, keeping "core" roles and tasks continuing to exist in the future, with the difference that they will be executed by AI technology [63,78]. There will also be new roles where collaboration with AI solutions will be necessary. Korzynsky et al. [18] consider AI Prompt Engineering as one of the future mandatory digital competencies when using GenAI. There is a major risk that poor prompt choice and formulation will render a GenAI-based system ineffective, which could influence the relevance and consistency of the results provided by AI models.

A significant risk for AI applications in general, and GenAI in particular, is algorithmic bias. Machine Learning algorithms identify patterns in the available data on which human decision-makers base their choices. If the pattern emerges due to a bias, the algorithms will amplify it and alter the results, exacerbating patterns of discrimination and the risk of ethical violations. In practice, the main instances of discrimination attributed to AI are caused by the following technical biases [79,80]: (i) bias generated by the distribution of the data used in model training, which does not respect the actual distribution of the data; (ii) sampling bias—resulting from the erroneous sizing of the sample used in model training; (iii) labelling bias—generated by the lack of diversity in the group of people labelling the training sample, with the data being altered by the biases of the labeller; (iv) proxy bias—generated by the inclusion of variables that are not directly related to the category being learned; (v) gender bias—induced by an algorithm that leads to gender discrimination; (vi) race bias—generated by an algorithm that leads to race discrimination. Interaction with the user can generate, in some situations, automation bias or confirmation bias, i.e., the tendency to more readily validate the results provided by an AI system under unconsciously developed automatisms [79]. Kirk et al. [81] showed that LLM can produce unethical, racist and sexist comments.

Another risk revealed in the literature [82,83] is that of the atrophy of people's skills—deskilling—who make decisions based more on the results provided by AI applications and less on their professional reasoning. Risks considered major are those associated with the security of accounting information [84], requiring accountants and auditors to be aware of and apply measures to ensure it. Understanding the mechanisms for encrypting data, anonymising sensitive and confidential information, securing networks and identifying potential threats and vulnerabilities is essential in maintaining data security. The authors of [85] also reported the potential of AI-enabled data analytic-driven audit tools to alter audit processes and raise concerns about their uncontrolled use by novice-level auditors. The adoption of AI systems may also involve legal risks to data privacy, requiring verification of compliance with the European Parliament's General Data Protection Regulation (GDPR), laws addressing discrimination (e.g., the US Civil Rights Act of 1964), any clauses in customer contracts, intellectual property regulations and personal information protection legislation adopted in some countries [86].

Following the scientific investigation, it appears that the relationship between the risks associated with the use of GenAI and the competencies of AA professionals may represent a future research direction, with the topic not being explored in the literature probably because of its novelty. The results confirm the necessity and usefulness of including, in the framework, elements that support organisations in their efforts to increase AA professionals' risk awareness, which can create the conditions for the development of specific KSAs.

3. Materials and Methods

The methodological approach was based on the Systematic Literature Review (SLR), which is considered a rigorous method for identifying, evaluating and synthesizing the existing body of knowledge in published materials by researchers and practitioners [87]. Embedding ideas advanced by Massaro [88] regarding the conduct of literature research in accounting into the three-stage model adapted from [87] investigating AI in the Industry 4.0 era, the study began with developing a general plan to guide the research, as shown in Figure 1.

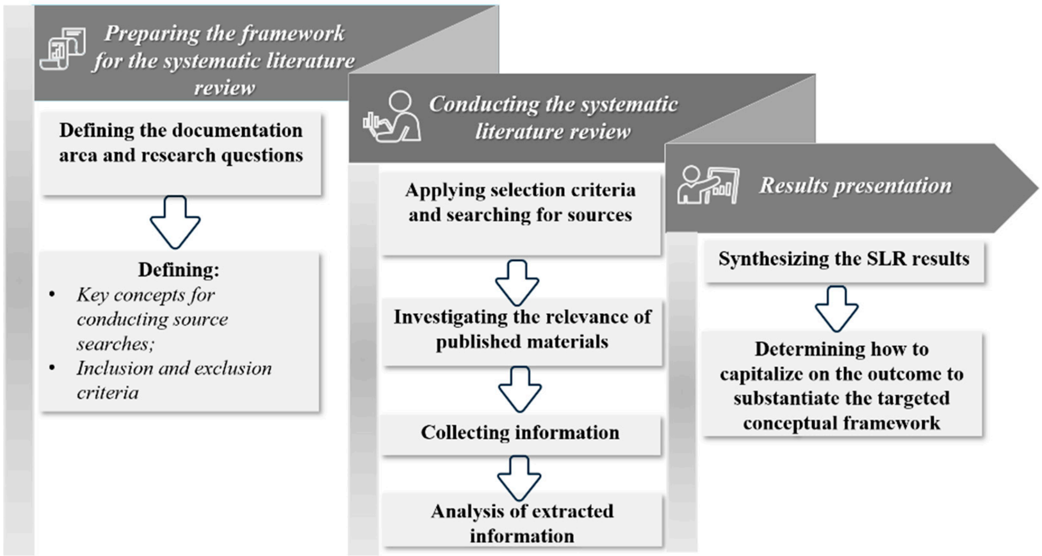

Figure 1. Overview of research methodology.

The area of research includes topics such as AI, GenAI, LLM and the required competencies in accounting and auditing. The next phase involved defining a twofold purpose of the study, aligned with the research questions to facilitate the orientation of the sources selection, the research running and the achievement of the study results. To answer the question "RQ1. What knowledge, skills and competencies are needed by accounting and auditing professionals to effectively leverage Generative Artificial Intelligence and what are the risks of using it in this field?", it was decided to conduct a search of the most recent papers in the Web of Science Core Collection, combined with an investigation of the business literature—an adapted PRISMA flow diagram (Figure 2).

The key concepts used in the design of the logical expression for locating relevant references in the emerging areas, executed at the level of titles, keywords and abstracts (topic) were determined: (("artificial intelligence" or "machine learning" or "deep learning" or AI or NLP or LLM or GPT or RPA) and ((competence*) or (skill*) or (knowledge*)) and (accountant or accountants or auditor or auditors))).

To improve the validity, reliability and rigor of the study contributions and conclusions, we also analysed documents produced by three global organisms and three national bodies, representative for the development of accounting and auditing professional standards and certifications: ACCA, CIMA, and IMA, respectively, and AICPA, ICAEW and ICAS (Table 1).

In the next step, the eligibility conditions—explicit inclusion and exclusion criteria—of the sources identified in the search were defined to create the prerequisites for an objective selection and a meaningful assessment of the research materials' relevance (Table 2). These criteria were derived from the study objectives and guided by the research questions.

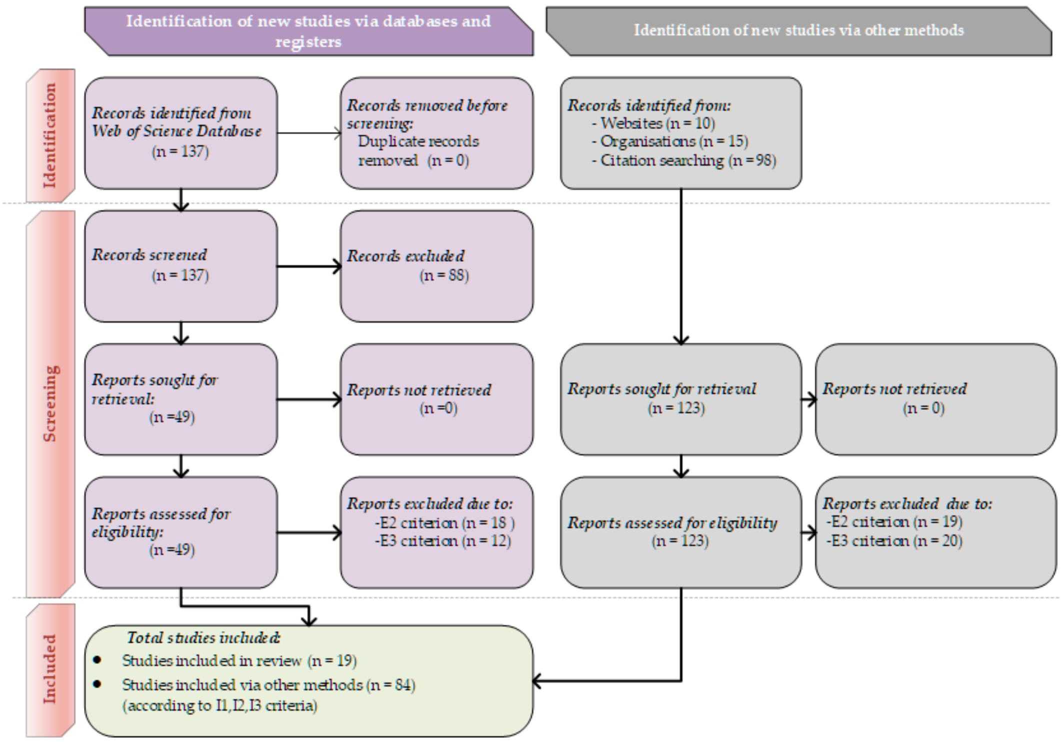

Figure 2. PRISMA flow diagram. Adapted from [89].

Table 2. Inclusion and exclusion criteria.

Criteria Type	Reason for Inclusion/Exclusion
Inclusion Criteria	(I1) The paper focuses on the need for the AA professional's competencies in AI/GenAI area (expected or required by the market). (I2) The paper focuses on the risks regarding AI/GenAI inclusion in AA domain. (I3) The paper focuses on GenAI/LLM in AA domain. (I4) The paper is a journal article, conference article or book chapter. (I5) The paper is published in English. (I6) The paper is published between 2018 and 2024.
Exclusion Criteria	(E1) No full text available. (E2) The paper does not address/focus on AA professional's competencies in relation to adopted AI technologies. (E3) The paper is only loosely related to AI/GenAI competencies for AA domain.

Applying the constraints resulted in obtaining an initial sample of 137 WoS-indexed articles, as can be seen in Table 3, the number of papers has increased significantly since 2019 due to both the novelty and rapid expansion of GenAI throughout the business world.

Table 3. Articles WoS by publication year.

Year	2018	2019	2020	2021	2022	2023	2024	Total
Papers Number	4	5	14	26	29	45	14	137

Each research team member checked the credibility and relevance of the identified references. Articles that did not address professional accounting and auditing skills concerning adopted AI technologies were eliminated. The final sample for our SLR includes 103 studies, a number considered relevant for an SLR approach [90].

Based on the SLR results, the second research question—"RQ2. How can organisations integrate Generative Artificial Intelligence capabilities into information systems to develop the skills of accounting and auditing professionals?"—redirected the scientific investigation to detect the consequences of the GenAI systems adoption on the competencies' development of accounting and auditing professionals and their assistance needs in current activities and decision-making processes. This effort finally resulted in developing a framework for integrating a GenAI-based system into the organisational environment. The sources considered relevant for the topic, and the main results extracted and harnessed in the construction of the proposed model were presented in Tables 4–6, as in [91,92].

Table 4. Articles selected from the WoS database, included in the final sample.

Reference	Article Title	Publication	Main Findings
Samiolo, et al., 2024 [83]	Auditor Judgment in the Fourth Industrial Revolution	Contemporary Accounting Research	Skills-related risks
Norzelan, et al., 2024 [63]	Technology Acceptance of Artificial Intelligence (AI) among Heads of Finance and Accounting Units in the Shared Service Industry	Technological Forecasting and Social Change	AI acceptance in finance and accounting; risk assessment
Arnold, et al., 2023 [82]	Can Knowledge Based Systems Be Designed to Counteract Deskilling Effects?	International Journal of Accounting Information Systems	Risks of deskilling; knowledge-based systems implications in supporting accounting professionals
Rawashdeh, 2024 [12]	A Deep Learning-Based SEM-ANN Analysis of the Impact of AI-Based Audit Services on Client Trust	Journal of Applied Accounting Research	AI-based audit services, perceived quality, value, attitude, satisfaction and trust
Munoko, et al., 2020 [7]	The Ethical Implications of Using Artificial Intelligence in Auditing	Journal of Business Ethics	Accounting and auditing industry interest in AI adoption
Thottoli, 2024 [75]	Leveraging information communication technology (ICT) and artificial intelligence (AI) to enhance auditing practices	Accounting Research Journal	Potential benefits and risks associated with AI and information communication technology (ICT) adoption in auditing
Jemine, et al., 2024 [60]	Technological innovation and the co-production of accounting services in small accounting firms	Accounting Auditing & Accountability Journal	Impact of emerging information technologies onto small accounting firms and professionals' competencies
Grosu, et al., 2023 [3]	Testing accountants' perceptions of the digitization of the profession and profiling the future professional	Technological Forecasting and Social Change	Challenges, knowledge and skills required to face technological evolution
Rodgers, et al., 2023 [20]	Protocol Analysis Data Collection Technique Implemented for Artificial Intelligence Design	IEEE Transactions on Engineering Management	Impact of the lack of an AI framework, IFRS knowledge, and legislation conflict on AA standards implementation; AI-based support for protocol analysis, benefits and designed features
Koreff, et al., 2023 [85]	Exploring the Impact of Technology Dominance on Audit Professionalism through Data Analytic-Driven Healthcare Audits	Journal of Information Systems	Potential of AI-enabled data analytic-driven audits tools to alter audit missions and derived concerns for their uncontrolled use by novice-level auditors
Ng, 2023 [50]	Teaching Advanced Data Analytics, Robotic Process Automation, and Artificial Intelligence in a Graduate Accounting Program	Journal of Emerging Technologies in Accounting	Reshaping skill sets needed in the accounting profession by designing courses that incorporate RPA and AI at a public university (USA)
Kommunuri, 2022 [8]	Artificial Intelligence and the Changing Landscape of Accounting: A Viewpoint	Pacific Accounting Review	The impact of AI and ML on the accounting skills environment

Table 4. *Cont.*

Reference	Article Title	Publication	Main Findings
Andiola, et al., 2022 [59]	Wealthy Watches Inc.: The Substantive Testing of Accounts Receivable in the Evolving Audit Environment	Issues in Accounting Education	Awareness of technologies used in audit practice; the case of students practicing scepticism and applying professional judgment using AI and RPA tools
Friedrich, et al., 2022 [6]	Epistemological Thinking about Accounting in the Era of Artificial Intelligence	Revista Gestao Organizacional	Links between accounting science and disruptive technologies; transformation of accounting science on report creation, interpretation and authentication
Fotoh and Lorentzon, 2021 [9]	The Impact of Digitalization on Future Audits	Journal of Emerging Technologies in Accounting	Competitivity framework for audit profession; need for new capabilities, skills and business models incorporating digital technologies
Mancini, et al., 2021 [55]	Four Research Pathways for Understanding the Role of Smart Technologies in Accounting	Meditari Accountancy Research	Mapping KSAs required to manage decision-supporting information by leveraging AI and other new technologies.
Leitner-Hanetseder, et al., 2021 [78]	Profession in Transition: Actors, Tasks and Roles in AI-Based Accounting	Journal of Applied Accounting Research	Changes for competencies for accounting professions and "core" roles; AI-based accounting context (mixed AI and human accounting teams).
Kirk, et al., 2021 [81]	Bias Out-of-the-Box: An Empirical Analysis of Intersectional Occupational Biases in Popular Generative Language Models	Advances in neural information processing systems	Risks of producing unethical, racist and sexist comments
Andreassen, 2020 [49]	Digital Technology and Changing Roles: A Management Accountant's Dream or Nightmare?	Journal of Management Control	Accountant new skills
Li and Liu, 2020 [25]	Development of an Intelligent NLP-Based Audit Plan Knowledge Discovery System	Journal of Emerging Technologies in Accounting	Generative Artificial Intelligence overview
Plumlee, et al., 2015 [58]	Training Auditors to Perform Analytical Procedures Using Metacognitive Skills	The Accounting Review	New skills required for auditors

Table 5. Selection of articles identified via other methods and some findings relevant to the proposed framework.

Reference	Article Title	Publication	Main Findings
Wölfel, et al., 2024 [93]	Knowledge-Based and Generative-AI-Driven Pedagogical Conversational Agents: A Comparative Study of Grice's Cooperative Principles and Trust	Big Data and Cognitive Computing	Generative Language Models (GLMs), PEdagogical conversational Tutor with generative AI component and adaptation
Dong, et al., 2024 [94]	An Automated Multi-Phase Facilitation Agent Based on LLM	IEICE Transactions on Information and Systems	LLM-based agent implementation; large-scale discussion support systems
Trad and Chehab, 2024 [36]	Prompt Engineering or Fine-Tuning? A Case Study on Phishing Detection with Large Language Models	Machine Learning and Knowledge Extraction	Prompt Engineering process; tailoring LLM to particular tasks

Table 5. *Cont.*

Reference	Article Title	Publication	Main Findings
White, et al., 2023 [37]	A Prompt Pattern Catalog to Enhance Prompt Engineering with ChatGPT	ArXiv	ChatGPT; Prompt Engineering
Floridi, 2023 [43]	AI as Agency Without Intelligence: On ChatGPT, Large Language Models, and Other Generative Models.	Philosophy & Technology	AI systems, AI2AI interoperability; "Confederated AI"
Piktus, 2023 [44]	Online Tools Help Large Language Models to Solve Problems through Reasoning	Nature	LLM-based systems and external data sources; how to improve LLMs' output
Wei, et al., 2022 [40]	Chain-of-Thought Prompting Elicits Reasoning in Large Language Models	International Review of Economics & Finance	Chain-of-Thoughts (CoT) prompting-requesting and providing the reasoning steps.

Table 6. Reports published by professional bodies, other research institutes and companies.

Reference	Article Title	Organisation Name	Main Findings
IMA, 2023 [74]	IMA Management Accounting Competency Framework		Core competencies considered by each professional body; analysing the gap associated with newly emerging requirements for accountants' and auditors' competencies generated by the integration of AI/GenAI/LLM solutions
ICAS, 2023 [73]	ICAS Mapping Our New Competencies		
AICPA & CIMA, 2022 [72]	CGMA Competency Framework		
ACCA, 2020 [71]	ACCA Competency Framework		
ICAEW, 2018 [70]	ACA Qualification Professional Development Ladders		
Mordor Intelligence, 2024 [10]	AI In Accounting Market Size & Share Analysis—Growth Trends & Forecasts (2024–2029)	Mordor Intelligence	Analysis of the AI in the accounting services market
McKinsey, 2023 [95]	The economic potential of generative AI: The next productivity frontier	McKinsey	The impact of GenAI on productivity
Alan Turing Institute, 2023 [48]	AI Skills for Business Competency Framework	Alan Turing Institute	Developing strategies to upskill staff using AI solutions
Schwartz, et al., 2022 [80]	Towards a Standard for Identifying and Managing Bias in Artificial Intelligence	National Institute of Standards and Technology	Technical biases and discrimination instances attributed to AI
OECD, 2019 [23]	Principles for trustworthy AI	OECD	Cooperation governments-stakeholders so that people hold the necessary competencies to interact effectively with AI tools

The tables presenting the main sources and findings selected for the study were organised by the search method used and arranged from the most recent to the oldest. Table 4 is more focused on our topics of AI/Gen AI adoption in the AA field, the need for AA professionals for new skills and competencies, the associated risks and the deduced research gaps.

Table 5 highlights a selection of the sources providing more technical findings related to LLM-based GenAI tools.

Table 6 lists the publications issued by international and national professional standard-setting bodies. These publications were reviewed to identify the core competencies and gaps resulting from the integration of emerging technologies in the AA domain. Five additional reports were included to demonstrate findings related to the AI-enhanced market for AA services, its impact on productivity and AI-related strategies for upskilling staff.

4. Results

To answer the first research question, we identified in the academic literature a set of core competencies for using GenAI in accounting and auditing, and we structured them into two categories:

1. Cross-disciplinary skills:
   - digital skills (data analytics skills, skills in extracting, managing and centralising the datasets provided to the system) [49,52,55];
   - prompt engineering skills (train the AI according to specific user needs) [37,78];
   - soft skills (communication and motivational capabilities, a holistic understanding of processes, project management skills [78], sceptical thinking and problem-solving) [58,59].
2. Profession-specific competencies:
   - transformation of accounting science on report creation, interpretation and authentication [6];
   - analysing historical internal structured data, collecting and selecting the data used for valuation [78];
   - forecasting and making audit decisions [25];
   - risk identification, risk assessment and risk mitigation [78];
   - the preparation of reporting elements; good accounting and business ethics knowledge; understanding of how the AI makes its decisions; supporting the management team in strategic planning and investment decisions [78].

In line with the trend of new disruptive technologies, the scientific literature highlights the growing need for advanced technical skills in the accounting and auditing profession, as opposed to the competencies frameworks established by professional accounting bodies (PABs). Looking ahead, it seems necessary for the PABs to update the competence of their underlying frameworks.

Analysing the context of using GenAI in the accounting and audit field, the main risks identified in the reviewed literature are the following:

- deskilling risks and their effects [82,83];
- model and bias risk [80];
- risks associated with the security of accounting information [84];
- risks related to AI-automated accounting functions [63];
- unethical, racist and sexist content generation by LLMs [81].

Considering the second research question, corroborating the literature review results, a framework was developed for integrating LLM-based GenAI systems with the IT systems of organisations providing accounting and auditing services. This approach aims to increase organisational performance by (1) automating repetitive tasks; (2) identifying anomalies, inconsistencies and potential risks in accounting records; (3) streamlining decision-making by providing data, information and predictive analyses; (4) continuously monitoring and complying with current accounting and auditing regulations; (5) developing organisational memory and improving organisational learning.

Although there are papers that have discussed the design of effective generative AI systems, such as [93], which proposed a GenAI conversational system model for pedagogical purposes, or [94], focusing on designing LLM-based agents for facilitating discussions, we have not encountered specific studies proposing a framework for effectively integrating generative artificial intelligence in accounting and auditing.

4.1. Framework for Integrating LLM-Based Internal GenAI System

The proposed model builds upon research conducted by [27,33,96–98], in the field of integrating GenAI in various domains. This research is supported by the engineered prompting and fine-tuning techniques analysed and described by [35–38]. It also incorporates Floridi's research [43] on AI-type inter-system communication (AI2AI) and Piktus's research [44] on combining the capabilities of LLM-based systems with external data sources. These contributions helped define some of the framework's main components.

The core element of our framework for integrating GenAI into the accounting and auditing field, the Knowledge Consolidator, plays a pivotal role in an LLM-based system. This component is an original contribution designed to continuously consult both external (websites, public or private databases, etc.) and internal (databases, data repositories, organisational memory, etc.) data sources. The need to integrate the Knowledge Consolidator component in the proposed framework is supported by prior research [99–101], which investigated the relationship between knowledge generation and AI-based models. Thus, AI can generate knowledge that can improve the reasoning of generative models and their compositional capabilities. In the framework, Knowledge Consolidator is designed to continuously extract and integrate information or knowledge into the System Data Source component, ensuring its relevance and up to date.

Consequently, the LLM-based internal GenAI system has three main components: the Large Language Model (LLM), the System Data Source and the Knowledge Consolidator (Figure 3).

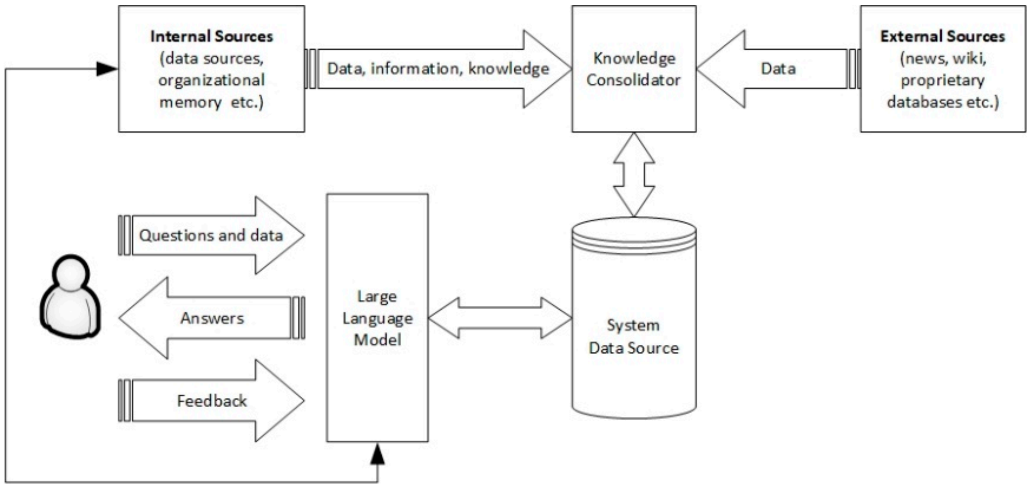

Figure 3. Framework for integrating an LLM-based internal GenAI system.

Following user requests, the System Data Source is queried by the LLM, providing answers or executing requested actions.

The way the user interacts with the LLM-based internal GenAI system is as follows:

1. The user addresses a question or requests an action to be performed and, if necessary, provides additional data to refine the context.
2. The system processes the text from the request and analyses any data provided to identify what the user wants or needs to do.
3. If applicable, the system queries internal sources based on the requirements/requests and data provided by the user.
4. Based on the processed text and data provided by the user or information obtained from internal sources using System Data Source, the system generates and displays a response or performs the requested action.
5. The user provides feedback on the system's response or action, which is used to learn and improve the internal GenAI system's performance over time by adjusting the processes of understanding, generating responses or taking the required action.

4.2. Extended LLM-Based Internal GenAI System

The framework described (Figure 3) could be further enhanced, resulting in an Extended LLM-based internal GenAI system that includes four main components: Filtering

(Security) Layer, Large Language Model (LLM), System Data Source and Knowledge Consolidator (Figure 4). The Knowledge Consolidator component behaves the same way as the original internal LLM-based GenAI system.

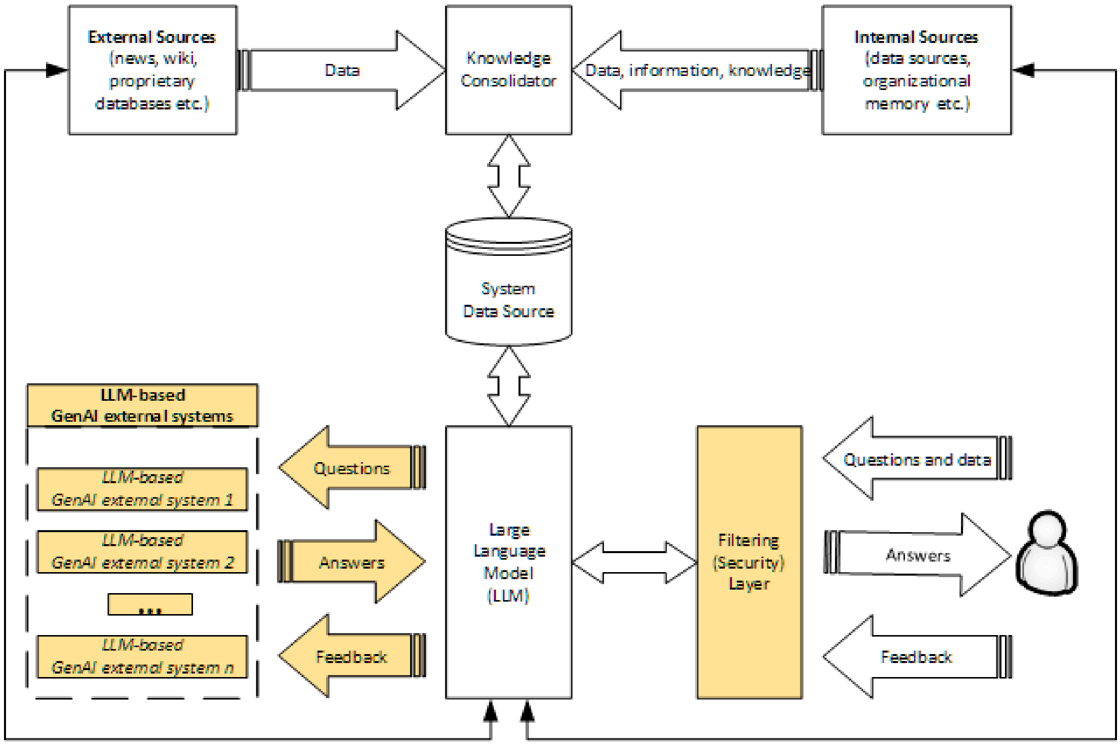

Figure 4. Framework on the integration of an extended LLM-based internal GenAI system.

The Extended LLM-based internal GenAI system has two major improvements:

1. The Filtering (Security) Layer, whose main role is to ensure the security and confidentiality of internal data and not to allow data and information to be transmitted externally by filtering queries and data transmitted outside the organisation. Considering that a significant part of the data managed by accountants and auditors is sensitive or confidential, it is mandatory to implement a filtering layer that prevents intentional or accidental transmission outside the internal system.
2. Continuous interaction with other LLM-based GenAI systems to improve the quality of the provided answers. This interaction enriches and extends the System Data Source by incorporating data from these systems.

Following user requests, the LLM queries the system data source and other LLM-based GenAI systems to provide answers or execute requested actions.

The way the system interacts with the user is as follows:

1. The user addresses a question or requests an action to be performed, possibly providing data to the system.
2. The system processes the user request and any related data.
3. The Filtering (Security) Layer performs filtering of it and of data provided by the user, sending to the LLM component two requests:
   (i) a prompt containing the request and the data submitted by the user that will be used to consult the system's data sources as well as internal and external sources;
   (ii) a prompt in which any confidential elements and data provided by the user have been removed from the request.
4. To understand the context of the user's request, the extended LLM-based internal GenAI system analyses related data provided by several advanced techniques.

5. If necessary, the system formulates a request to internal or external sources based on the requirements and data provided by the user.
6. The system consults in parallel:
   (i) System Data Source based on processed text and user-supplied data.
   (ii) Internal or external sources.
   (iii) Other external LLM-based GenAI systems based on text processed and filtered by the Filtering (Security) Layer component. These systems can be public or non-public. Non-public systems can be accessed based on an inter-organisational cooperation agreement and represent a component of the learning process through exchanging knowledge, experience and resources.
7. The system generates and displays a response or performs the requested action.
8. The user provides feedback on the response received from the system or the undertaken action, which is used for learning and improving the performance of the internal system over time by adjusting the processes of understanding, generating responses or taking the required action. Depending on the organisation's policy, the system may also provide feedback to the consulted external LLM-based GenAI systems.

Figure 5 shows the process of using (modus operandi) the LLM-based internal GenAI system in terms of the competencies leveraged and knowledge gained. The response returned by the system will be subject to a content check and analysed by the person using it. Professional judgement will be the key competence to detect certain anomalies or vulnerabilities in the output. At this stage, the same set of profession-specific competencies will be called upon [70–74], coupled with others which fall within the sphere of personal cognitive skills, such as critical thinking [58]. Also, in the category of cognitive competencies, the ability to recognise and be aware of the risks associated with the results obtained [79,84,86] will enable the accountant or auditor to qualify them as acceptable or inappropriate. The use of Chain-of-Thoughts and Role-Playing techniques [40,41] in the prompting stage can have positive effects in increasing the relevance of GenAI system responses to user expectations.

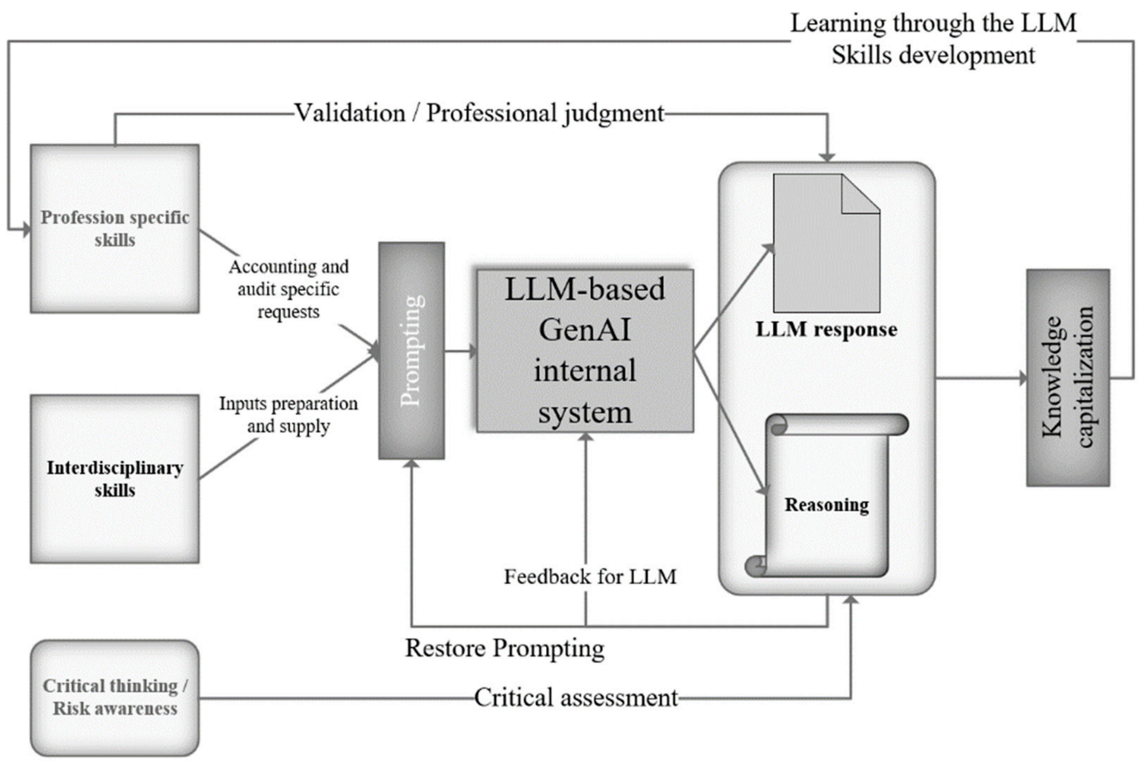

Figure 5. The correlation between competencies and results for using LLM-based internal GenAI system in accounting and auditing.

The validation stage of the outputs provided by the system can result in either accepting the answer or refining the prompt and restarting the process [37]. In the latter case, the LLM will receive feedback concerning why the response cannot be considered acceptable. The new knowledge generated by the LLM-based system will be capitalised and can form an important basis for developing employees' professional skills and competencies.

5. Discussion

Although GenAI is attracting interest from researchers and practitioners because of its vast potential to revolutionise lifelong learning and competencies development, only a few studies are addressing how to integrate GenAI into accounting and auditing. Integrating LLM-based GenAI into organisational information systems is a novel element that contributes to the accounting and auditing research field. This framework enables human-machine collaborations, focusing on AA professionals' competencies, upskilling and reskilling and fostering a culture of continuous learning.

5.1. An Explanatory Scenario

To help readers better understand the proposed framework outlined above, we will illustrate its underlying functional logic with a descriptive example of a hypothetical financial audit mission.

The Audit Services is a company that provides financial audit services. During the audit mission, daily, each team member enters relevant data and information into the internal system. After the completion of the mission, a meeting is scheduled to discuss the main issues encountered and how they were solved. The relevant data, information and knowledge are recorded in the internal system. On the other hand, the company has a tool (Knowledge Consolidator) that continuously performs three main tasks: (1) collects data from the internet (online databases, news sites, competitors' sites, social media and other relevant portals); (2) extracts and transforms data, information and knowledge from the internal system; and (3) feeds data sources into the system based on the results of (1) and (2). At the same time, the company has some agreements with other companies in different industries to interconnect their LLM-based GenAI external systems to enhance the capabilities of the internal GenAI system.

A new audit mission has been started for Best Transport Services that provides domestic and international transportation services by trucks. Helen (one of the team leaders of the audit mission) will formulate a few questions to addressed in the GenAI system. The first question may be, "What are the sensitive issues in auditing a company from the transportation area?". The system will query the system's data source and communicate with the other LLM-based GenAI external systems to provide the best answers to the question. Based on the answer received, Helen will further address two questions: "Has the Best Transport Services been involved in major road events in the last year?", "How many transport vehicles have been insured in the last year?". Assuming the answers were "Best Transport Services has been involved in two major events, both abroad" and "Best Transport Services has insured 59 trucks", Helen can require more data and documents related to these events, and, on the other hand, she can ask for more data on the company's transport vehicle insurance process, insurance policies and payments to insurance companies.

In the pre-audit stage, Helen receives from the transport company the set of financial documents for the audited period in electronic format (many of them in datasheet format). Since the quality of the training data heavily influences the outputs, she organises them into datasets with financial significance that she will use in the LLM-based GenAI system training process. Helen will ask the LLM-based GenAI system what correlations can be identified between the analysed incidents and the company's operational activity regarding costs and possible reductions in orders from clients. By analysing the reasoning used and provided by the GenAI system based on the LLM, Helen will remove the inconclusive results by leveraging her expertise in the audit field. Helen will use fine-tuning techniques to address in-depth questions about specific aspects. This will involve highlighting various data sources (internal and/or external) such as insurance prices, the bonus-malus system of partner insurance companies, the history of previous incidents or similar situations at companies in the same field of activity. The system will be able to identify new correlations and provide conclusions in the analysed case. At the same time, Helen will enter the final audit report into the system along with relevant feedback regarding the information received from the GenAI system. Building this knowledge base will allow the system to handle future queries on similar matters more effectively.

Figure 6 illustrates the described scenario using a Business Process Modeling and Notation (BPMN) diagram to help understand how the LLM-based GenAI integrates in the hypothetical financial audit mission.

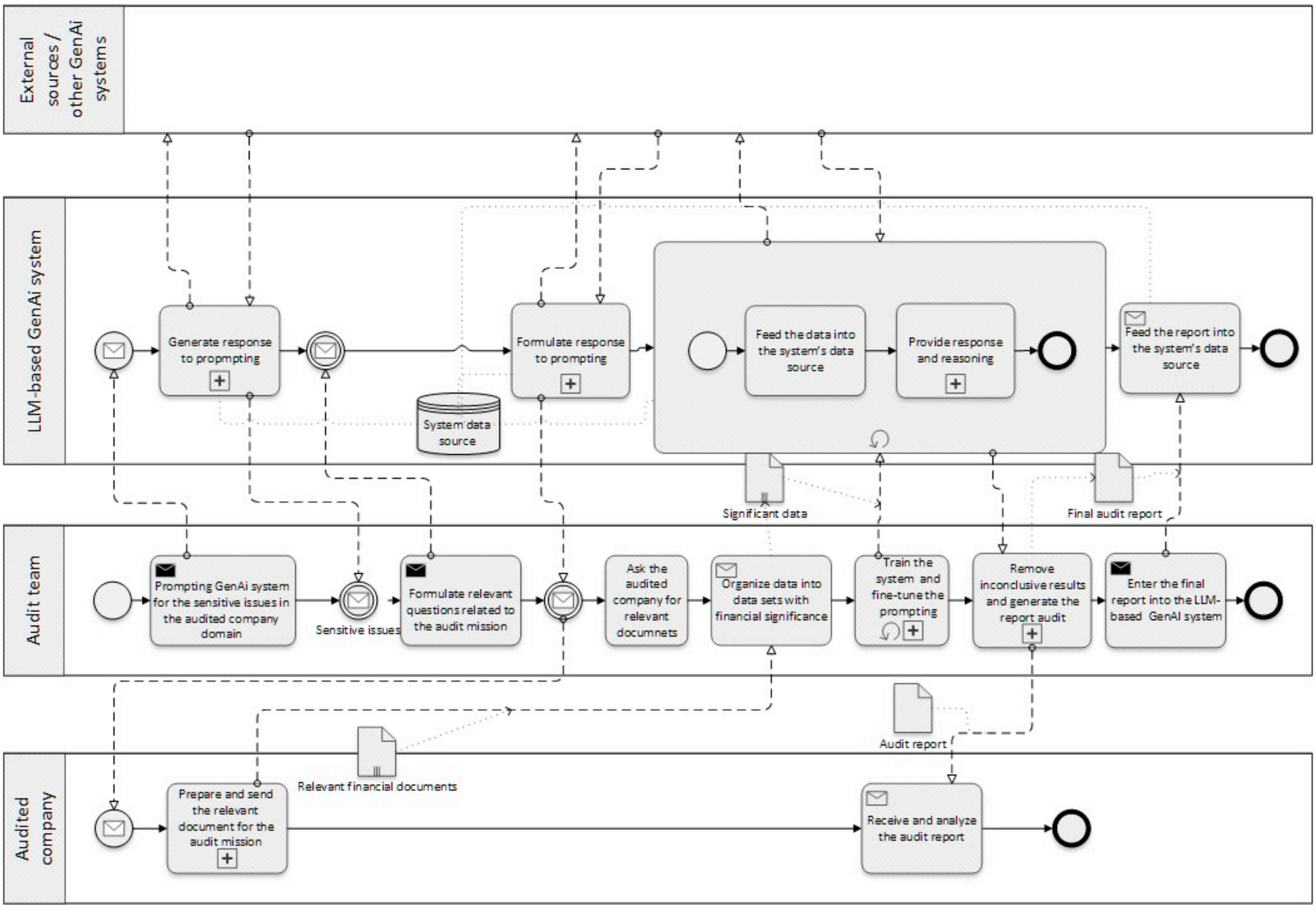

Figure 6. BPMN diagram for the explanatory scenario.

5.2. Benefits of Integrating LLM-Based GenAI Systems in Developing Competencies for Accounting and Audit Professionals

According to McKinsey (2023) [95], the impact of GenAI on productivity has the potential to generate the equivalent from USD 2.6 trillion to USD 4.4 trillion annually and increase the impact of artificial intelligence by 15–40 percent.

Leveraging the proposed framework, it is possible to build an internal GenAI system based on LLM, which fulfils a dual role: (1) redefining how AA professionals can acquire new knowledge and develop necessary skills and (2) assisting them in their current professional activities and during decision-making processes.

5.2.1. Redefining How AA Professionals Can Acquire New Knowledge and Develop Necessary Skills

GenAI has the potential to determine the increase in labour productivity [95], which is significantly influenced by employees' learning and development [102]. Among the benefits offered by the internal GenAI system in the process of learning and development of employees' skills are:

1. Providing personalised learning pathways following the analysis of each employee's KSA, learning preferences and career goals [103–105].
2. Preparation of learning materials by reviewing a significant volume of internal and external resources and selecting those relevant to each employee [106].
3. Adaptive learning, by dynamically adjusting the difficulty level and pace of presentation of learning materials according to the learner's progress and performance [107], which can lead to a stimulation of the creativity of each employee [104].
4. Assessing employees' skills and knowledge by various means, providing timely and actionable feedback on performance [104,108]. Because feedback supports learning achievement [104], it is a huge benefit for employees to receive valuable and timely feedback.
5. Virtual coaching and mentoring throughout the learning process (interactive conversations and simulations that allow employees to practice and hone their skills) [109,110]. In 2012, the McKinsey Global Institute (MGI) estimated that knowledge workers spent about 20% of their time to search and to gather information [95]. GenAI's support can drastically reduce this time, followed by a significant increase in employee efficiency and effectiveness.
6. Continuous learning and knowledge capitalisation by facilitating the exchange of information, best practices and lessons learned, enriching organisational memory [111,112].

On the other hand, there are concerns regarding the propagation of misinformation by GenAI systems [105,113], continuous monitoring of the answers provided by the GenAI system and the feedback provided by the employees is mandatory.

5.2.2. Assisting Current Activities and Decision-Making Processes

The benefits of targeted GenAI systems converge towards:

(i). Information retrieval and synthesis based on employee's expertise and requirements [110].
(ii). Assistance during the decision-making process [114], while, at the same time, allowing for transparency (GenAI system's decision-making process is visible to employees) and explainability (GenAI system's decisions are easy to understand by employees) [115].
(iii). Collaboration and communication across the organisation, fostering a collaborative environment [116].
(iv). Automation and support for routine/repetitive tasks, assistance, recommendations and suggestions [111].

This study has several limitations worth noting. Due to the paper topic's novelty, the sample of academic articles obtained from the search in the WoS database was not as extensive as expected. In addition, searching the literature sources, choosing terms in the search string and using exclusion criteria were based on subjective assessments and carry the risk of not identifying all relevant publications. Future research should consider increasing the sample size for more reliable and generalisable results.

Moreover, the reviewed papers on the GenAI topic focus mainly on the technical aspects of this disruptive technology. While this is valuable for understanding the fundamental principles of LLM-based system components, a potential limitation is the absence of information regarding their real-world implementation and outcomes.

6. Conclusions

The labour market is continuously adapting to changes in the business environment, looking for professionals with skills appropriate to the diversified contexts generated by AI technologies in organisations. The literature review analysis confirms a demand for new skills in the AA labour market. Research on the competencies needed by accounting and audit (AA) professionals has examined academic and technological perspectives, focusing on the skills required for graduates and the impact of AI/GenAI technologies on the labour market [77].

The integrative approach of GenAI technology in accounting and auditing represents an original contribution to the body of knowledge with theoretical and practical implications. Based on the proposed framework, an internal LLM-based GenAI system can, in our opinion, support AA professionals by reshaping the way they acquire knowledge and skills and assisting them in their professional activities and decision-making processes. It can improve analytical understanding and awareness of how GenAI can work with the accounting and auditing profession, representing, in our view, a starting point in integrating this innovative technology into operational and decision-support activities.

On the theoretical side, the study provides insights into the requirements for new skills accountants and auditors need to leverage GenAI technologies in their professional work. Equally, the elements of the framework for integrating GenAI can be adapted to the specific contexts of related (tax, valuation, business analysis) or different areas. The paper also brings to the fore the benefits of lifelong learning, which converge towards developing competencies by capitalising on the knowledge resulting from the use of GenAI at the organisational level. The practical implications of the research are positioned in the accounting–auditing–GenAI confluence area. The proposed framework offers insight into the complexity and nature of GenAI technology, as well as the skills required to manage it.

Answering the first research question, the paper reveals the necessity for professional training of staff to develop competencies aimed at (i) elaborating effective prompts for information, (ii) interpreting answers, (iii) awareness and correct treatment of the risks involved and (iv) reconfiguring the role of technical and social competencies that AA professionals could use in specific or decision-making activities, compared to other competencies considered so far as a priority.

Upcoming research could study the discrepancies between the demand and supply of competencies related to the accounting and auditing professions in the GenAI integration context. Equally, modelling organisational learning tools dedicated to the accountability of AA professionals regarding the risks associated with the GenAI use may raise the interest of both researchers and practitioners in the future. Furthermore, developing new domain ontologies, with the capability to integrate and leverage the results of the LLM-based GenAI system and to systematically enrich organisational acquis, could constitute another direction of future research. Such tools could ensure a meaningful knowledge base for daily operations and a real-time platform for continuous learning for both young professionals and experienced specialists in the accounting and audit area.

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