MARCO SCHREYER
TARJA MÄDER
T. FLEMMING RUUD

A NOVEL DIGITAL AUDIT WORKFORCE

Embedding Agentic Artificial Intelligence in Internal Auditing

Agentic artificial intelligence (AI) enables auditors to partner with autonomous AI systems that perceive, reason, act, and learn independently. These systems promise to expand audit coverage, streamline evidence collection, and generate insights throughout the audit lifecycle. This article outlines agentic AI's foundations and illustrates its practical benefits.

1. INTRODUCTION

In recent years, the world has marvelled at the capabilities of generative artificial intelligence (AI), and of large language models (LLMs), often referred to as foundation models [1]. These models can perform diverse tasks such as translation, summarisation, and coding based on textual prompts [2]. The next phase of AI promises an even greater transformation [3]. The evolution is shifting from *AI-enabled tools* to *AI-enabled agents* that leverage foundation models to execute complex, multistep workflows, representing a significant leap forward from traditional LLMs [4]. While language models act as *copilots*, generating valuable content upon request [5], AI agents serve as *autopilots*, autonomously executing complex tasks to achieve defined goals [6]. With minimal human oversight, they can independently perform tasks, devise actionable plans, and interact with external tools such as search engines, spreadsheets, and proprietary applications [7].

Integrating AI agents into various sectors marks the next step in a rapidly advancing technological landscape [8]. Noteworthy advancements include Google's initiative in 2022 to create a generalist AI agent (named *GATO*) for performing a wide range of tasks across different domains that included playing games, captioning images, and controlling robots [9]. In 2023, *Auto-GPT* was released as an open-source AI agent that, given a goal in natural language, will attempt to achieve it using the internet and other tools in an automatic loop [10]. In 2024, Anthropic introduced *Computer Use* [11], a system-level AI capable of navigating software interfaces autonomously, and Cognition.AI launched *Devin* [12], the first AI software engineer. The emergence of AI agent standards like Anthropic's *Model Context Protocol* [13], announced at the end of 2024, enhances this evolution by providing a universal interface enabling AI agents to access and interact with diverse enterprise systems and data sources. In January 2025, OpenAI released *Operator* [14], an AI agent designed to execute user tasks. ManusAI recently unveiled *Manus* [15], an autonomous AI agent capable of performing complex real-world tasks without direct human guidance.

According to Gartner, autonomous agents are expected to impact various industries [16], including auditing. When testing internal controls in the procure-to-pay process, for example, AI agents can autonomously verify approvals, match purchase orders with invoices and receipts, detect anomalies, and ensure policy compliance [17]. They interact with human auditors in natural language throughout the process, thereby improving the auditors' efficiency [18]. Integrating AI agents promises to transform the internal auditing lifecycle. This article offers an initial perspective on embedding AI agents into internal auditing.

2. ARTIFICIAL INTELLIGENCE AGENTS

An *agent* denotes a physical or a virtual entity that can act, perceive its environment, and communicate with others [19]. In the context of AI agents, *agency* refers to the capacity of an artificial system to operate autonomously, making independent decisions to achieve predefined objectives without

MARCO SCHREYER, PHD, AUDIT SPECIALIST, SWISS FEDERAL AUDIT OFFICE (SFAO), POSTDOCTORAL DAAD IFI RESEARCH FELLOW, INTERNATIONAL COMPUTER SCIENCE, INSTITUTE (ICSI), BERKELEY

TARJA MÄDER, LIC. OEC. HSG, DATA ANALYST INTERNAL AUDIT, CERTIFIED INTERNAL AUDITOR (CIA)

Figure 1: **CONVENTIONAL SOFTWARE AGENT GOVERNED BY A SOFTWARE PROGRAM VS. ARTIFICIAL INTELLIGENCE AGENT GOVERNED BY A LARGE LANGUAGE MODEL** [27]

constant human intervention. This encompasses the system's ability to perceive its environment. Perception is typically facilitated through sensors, while interactions with the environment are mediated via actuators [20]. For example, humans perceive through their eyes and ears and act via their hands and legs. Similarly, an agent processes inputs like keystrokes or network packets and responds through outputs such as displays.

An agent's behaviour is directed by an agent function, an abstract mathematical formulation that effectively serves as the agent's "brain". This function is typically implemented via an agent program operating within a physical system. In agentic AI, traditional agent functions are increasingly being replaced by sophisticated models, such as deep neural network-based LLMs [21]. *Figure 1* illustrates the difference between conventional software-governed agents and modern LLM-governed agents. This shift enhances agents' capabilities, enabling them to perform complex tasks autonomously and make informed decisions.

Artificially intelligent agents differ significantly from monolithic LLMs like GPT-4 [22], Llama [23], or Mistral [24]. While LLMs are knowledgeable, they generate responses based solely on the input they receive but lack the ability to initiate actions or make independent decisions. As a result, their lack of autonomy, inability to interact with external tools, and absence of long-term memory often limit their ability to complete real-world audit tasks [25]. In contrast, AI agents can autonomously achieve audit-related goals over an extended period through planning, memory, and tools [26].

→ *Planning:* AI agents break down large tasks into more minor, manageable subgoals using techniques like Chain of Thoughts, Tree of Thoughts, or LLM Planners. They engage in self-criticism and reflect on past actions, learn from mistakes, and refine future steps, thereby improving the quality of their outputs [28].

→ *Memory:* AI agents use short-term memory techniques like prompt engineering to adapt to new information during interactions [29]. They also have long-term memory capabilities that enable them to retain and recall extensive information over time, e.g., through retrieval-augmented generation from external data sources [30].

→ *Tools:* AI agents learn to call external applications for real-time data, code execution, and access to proprietary information sources. Tool use allows LLMs to extend beyond text generation and chatbot capabilities. Examples include HuggingGPT [31] and Toolformer [32].

Given these characteristics, AI agents excel in handling challenging, realistic tasks that often lack a single correct solution, offering real-world audit utility [33]. For internal auditors, leveraging AI agents can improve the efficiency, accuracy, and scope of their audit processes, enabling them to focus on higher-level analysis and decision-making.

3. ARTIFICIAL INTELLIGENCE AGENTIC AUDITING

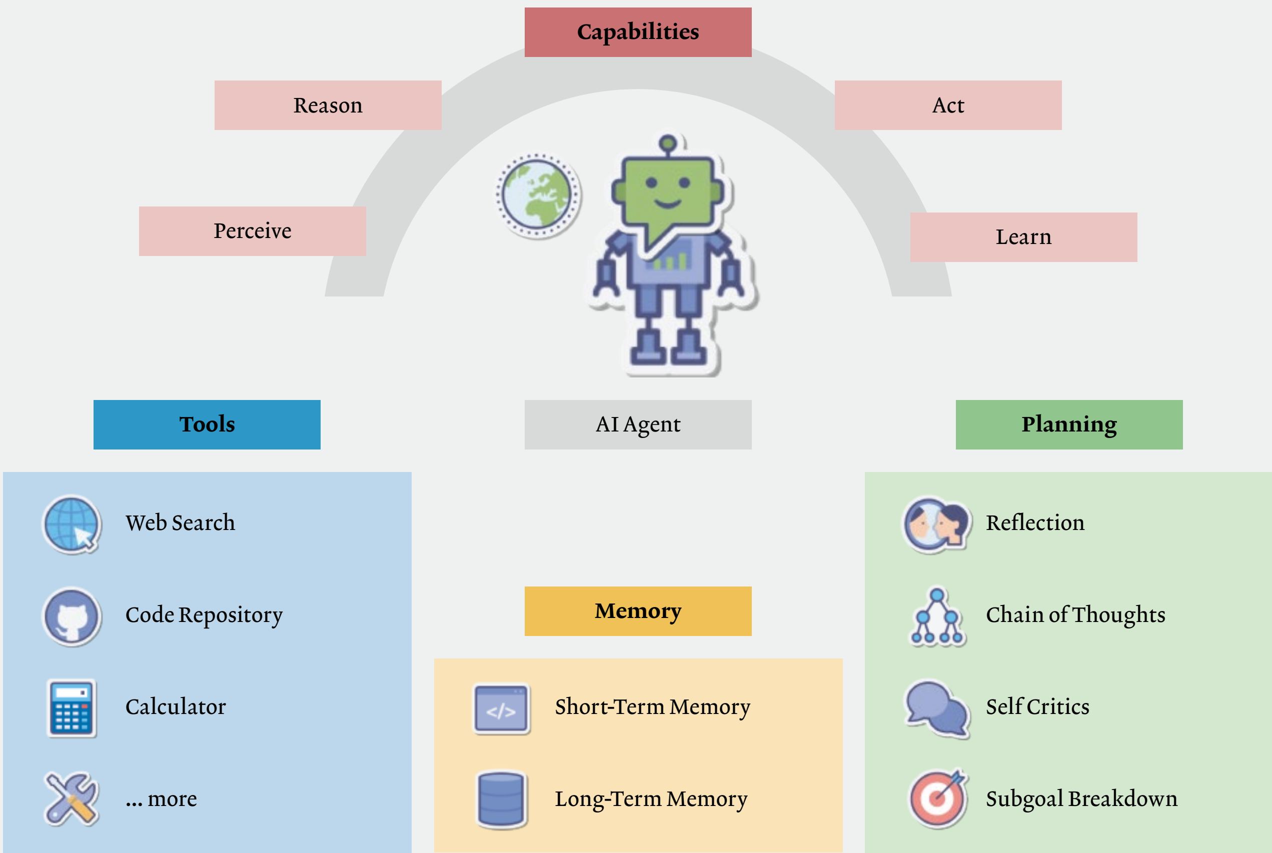
Artificial intelligence agentic auditing defines a transformation in how tasks can be administered and executed in internal auditing. Unlike traditional AI agents [34], which assist auditors in isolated tasks, agentic AI systems operate autonomously, guided by four core capabilities: (1) perceive, (2) reason, (3) act and (4) learn [35].

→ *Perceive:* Perception denotes the agent's ability to observe, gather, and interpret information from its environment. This includes recognising relevant data, identifying patterns, and contextualising inputs across modalities such as text, numbers, or sensor signals. Adequate perception capabilities enable the agent to maintain an up-to-date and accurate understanding of its operating context.

→ *Reason:* Reasoning refers to the agent's capacity to process information, form judgements, and make decisions based on logic or probabilistic inference. It involves drawing conclusions, identifying relationships, and prioritising actions to achieve goals. Strong reasoning allows the agent to operate

T. FLEMMING RUUD, PHD, CERTIFIED PUBLIC ACCOUNTANT (NORWAY), PROFESSOR OF INTERNAL & EXTERNAL AUDITING, BI NORWEGIAN BUSINESS SCHOOL, PROF. EM. UNIVERSITY ST GALLEN

Figure 2: **CONCEPTUAL ARCHITECTURE AND CORE FUNCTIONS OF AN AI AGENT**



coherently, even in the presence of uncertainty or incomplete information.

→ *Act:* Action denotes the agent's ability to interact with its environment through purposeful operations. This may involve triggering workflows, manipulating digital tools, or communicating outputs to other systems or agents. By acting autonomously, the agent can execute plans and influence its surroundings to achieve single or multiple predefined objectives.

→ *Learn:* Learning refers to the agent's ability to improve performance over time by incorporating feedback and updating its internal models. This can involve refining parameters, adapting strategies, or generalising based on experience gained in new situations. Learning makes the agent more effective, resilient, and aligned with its goals in dynamic environments.

These principles provide a foundation for integrating agentic workflows across the phases of the internal audit life cycle [36].

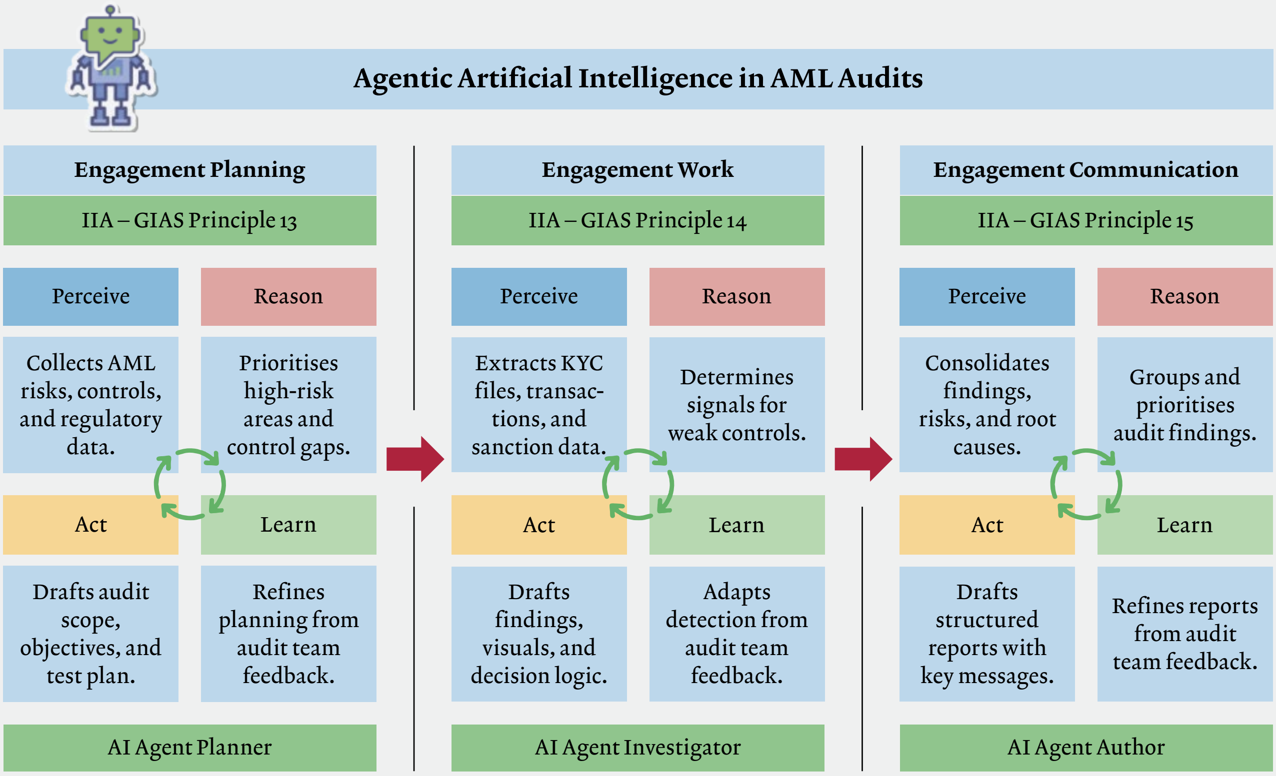
3.1 Embedding AI Agents in Internal Auditing. The Institute of Internal Auditors (IIA) defines internal auditing as "an independent, objective assurance activity designed to add value and improve an organisation's operations." [37] Internal auditing systematically evaluates an organisation's risk management, control, and governance processes to ensure compliance with established standards. According to the IIA's Global Internal Audit Standards (GIAS), audits follow a structured process consisting of the phases: engagement planning, engagement work and engagement communication.

The subsequent example illustrates how agentic AI can be embedded in anti-money laundering (AML) audits at a financial institution, across the phases of the audit lifecycle, as depicted in *Figure 3*.

3.1.1 Engagement Planning. According to IIA Principle 13 [38], effective engagement planning should be risk-focused, systematic, and aligned with organisational objectives. The planning process begins with understanding the rationale for including the engagement in the audit plan and collecting relevant information about the organisation and the area under review. Throughout the planning phase, internal auditors assess applicable risks, define the engagement's objectives and scope, identify key controls, and determine the resources required. In an AML audit, an AI agent applies its (1) perceive, (2) reason, (3) act and (4) learn capabilities to support and streamline the planning process.

→ *Perceive:* The AI agent gathers internal data such as AML risk assessments, past audit reports and incidents, control inventory and performance data, customer lists, and transaction records. It also collects external information, such as regulatory guidance, typologies, and industry benchmarks,

Figure 3: **AGENTIC AI IN AML AUDITS: CORE CAPABILITIES ALIGNED WITH IIA GIAS PRINCIPLES 13–15**



through web scraping and API connectors to build a comprehensive understanding of the risk landscape.

→ *Reason:* Based on this input, the agent detects and contextualises risk indicators, including spikes in high-value transactions, the presence of politically exposed persons (PEPs), low suspicious transaction report (STR) rates in high-risk branches, control gaps, and new AML regulations. It ranks these risks using decision-making algorithms and adaptive models in order to recommend audit priorities that are aligned with risk-based plans.

→ *Act:* Using its analysis, the agent drafts a planning memorandum in which it proposes the audit objectives, scope, and procedures. For example, it may recommend control testing in high-risk branches with low STR activity, assess the KYC file review process for hidden connections, or evaluate the institution's ability to adapt to new AML regulations by reviewing policies, procedures, and control updates.

→ *Learn:* After the engagement, the AI agent incorporates feedback from the audit team and fieldwork outcomes. It refines its internal models to improve risk identification and scope definition in future planning phases. Over time, this feedback loop ensures that the agent becomes increasingly aligned with the financial institution's evolving risk landscape and the professional judgment of its internal auditors.

These capabilities enable the AI agent to function as an intelligent *planner*. The phase results in an audit work program that outlines the procedures to be performed and serves as a roadmap for executing the audit.

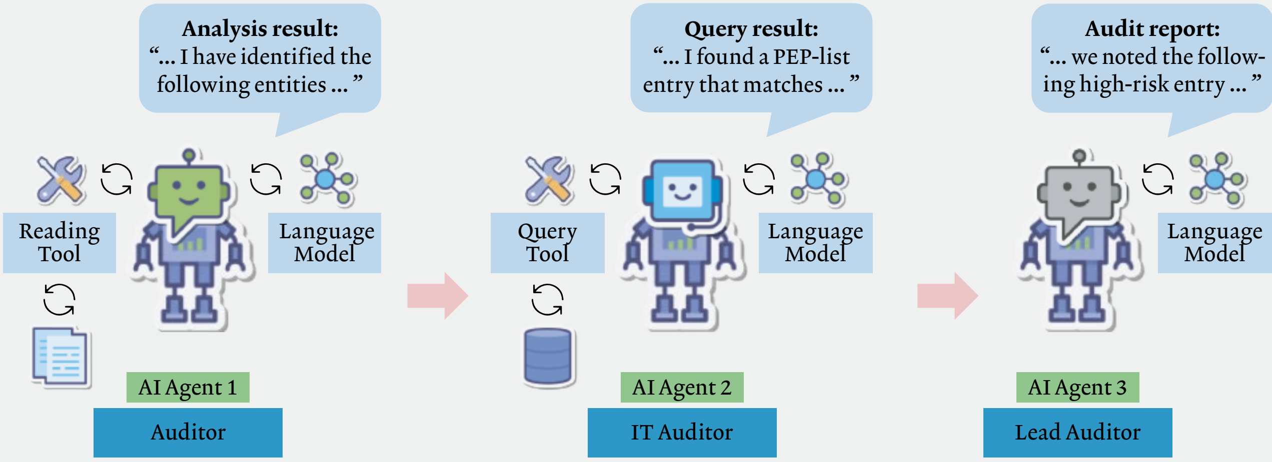
3.1.2 Engagement Work. According to IIA Principle 14 [39], engagement work involves gathering and analysing evidence to support audit findings and conclusions. Auditors implement the work program by collecting information, performing evaluations, and documenting results. In the fieldwork phase, internal auditors assess the causes, effects, and significance of findings and may collaborate with management on appropriate actions. In the AML audit example, an AI agent applies its capabilities throughout the evidence-gathering and evaluation process.

→ *Perceive:* The AI agent automates data collection from internal sources such as transactions, CDD/KYC files, system logs, internal policies, control executions, and interviews, and integrates external data like PEP or sanction lists. Throughout the audit, it uses natural language processing and data parsing tools to retrieve structured and unstructured data relevant to the audit scope.

→ *Reason:* The AI agent applies anomaly detection and clustering techniques to analyse transactional data for the purpose of highlighting suspicious activities, such as rapid fund transfers or inconsistencies with customer profiles. It also reviews KYC files to identify missing documents, outdated information, or textual indicators of elevated risk to ensure the operating effectiveness of controls.

→ *Act:* The agent compiles structured draft observations, visualises key indicators, and documents its decision-making logic. Draft findings are shared in dashboards or working papers. Once the auditor reviews these findings, the agent may autonomously send fact-checking queries to the auditee

Figure 4: **OVERVIEW OF THE AGENTIC AUDIT WORKFLOW INVOLVING THREE COLLABORATING AI AGENTS FOR CONTROL TESTING IN THE KNOW YOUR CUSTOMER (KYC) PROCESS** [42]



and continue drafting reports on a wide range of issues that include risk ratings, potential root causes, and initial recommendations.

→ *Learn:* As auditors review findings and flag false positives or provide context, the agent adapts its detection models to improve future performance. This feedback loop helps to reduce noise, to increase relevance, and aligns the agent's outputs closely with auditors' professional judgment and organisational expectations.

These capabilities enable the AI agent to function as an intelligent *investigator*. The phase results in a risk-aligned evidence base that supports the auditor's judgment and lays the groundwork for reporting and follow-up.

3.1.3 Engagement Communication. According to IIA Principle 15 [40], internal auditors are responsible for issuing a final communication upon completing the engagement and communicating the results to management. This communication includes the audit's objectives, scope, findings, conclusions, and recommendations or action plans, where applicable. The reporting phase ensures transparency, facilitates decision-making, and supports the organisation's accountability. In the AML audit example, an AI agent applies its capabilities to support the reporting process:

→ *Perceive:* The AI agent consolidates inputs from the audit's fieldwork, including control deficiencies, risk ratings, and root cause analyses. It gathers observation metadata – such as the affected business unit, associated AML control gaps, and severity scores – to ensure all reportable elements are included in the final draft.

→ *Reason:* The agent synthesises these inputs into structured findings and aligns them with AML regulatory expectations and internal audit frameworks. For example, it uses coherent themes to group related observations, such as systemic KYC file deficiencies or repeated STR underreporting in specific branches, thereby linking them to underlying risk categories.

→ *Act:* Using LLMs and predefined reporting templates, the agent drafts a report that includes an executive summary, detailed observations, and risk-graded recommendations. It selects and integrates tailored visualisations to reinforce key messages. A standards-aligned checklist validates the report's completeness and compliance with IIA requirements before it is reviewed by an auditor.

→ *Learn:* As auditors revise the content, tone, or structure, the agent records feedback to improve the next reporting cycle. For instance, if a visual is replaced due to audience misalignment or a summary section is reworded for clarity, the agent adapts its logic to comply with internal style and stakeholder preferences. It also references past AML audit reports to maintain reporting continuity across time.

These capabilities enable the AI agent to function as an intelligent *author*. The phase results in consistent, standards-compliant audit reports that strengthen communication and support follow-up actions.

3.2 Practical Case Study: Audit the Know your Customer Process. The following case study explores how internal auditing can leverage agentic AI systems to evaluate the effectiveness of controls in the Know your customer (KYC) process. While the underlying tasks are typically carried out by client onboarding (first line) or compliance (second line) functions, the audit tests the reliability and execution quality of these controls. A reference implementation of the described agentic workflow is open-sourced and publicly available on GitHub [41], along with usage instructions and sample data.

By deploying a team of specialised AI agents, internal auditors can simulate traditional AML audit roles, where each agent focuses on a specific process step or dataset [43]. The three specialised AI agents employed in the operating effectiveness testing of the KYC file review process assumed the following roles:

1. *Auditor Agent:* This agent analysed a comprehensive KYC file, extracting all individuals and entities and identifying

Figure 5: **INTERNAL REASONING EXCERPT FROM THE AML AUDITOR AGENT ON KNOW YOUR CUSTOMER (KYC) FILE EXTRACTION USING THE READ FILE TOOL**

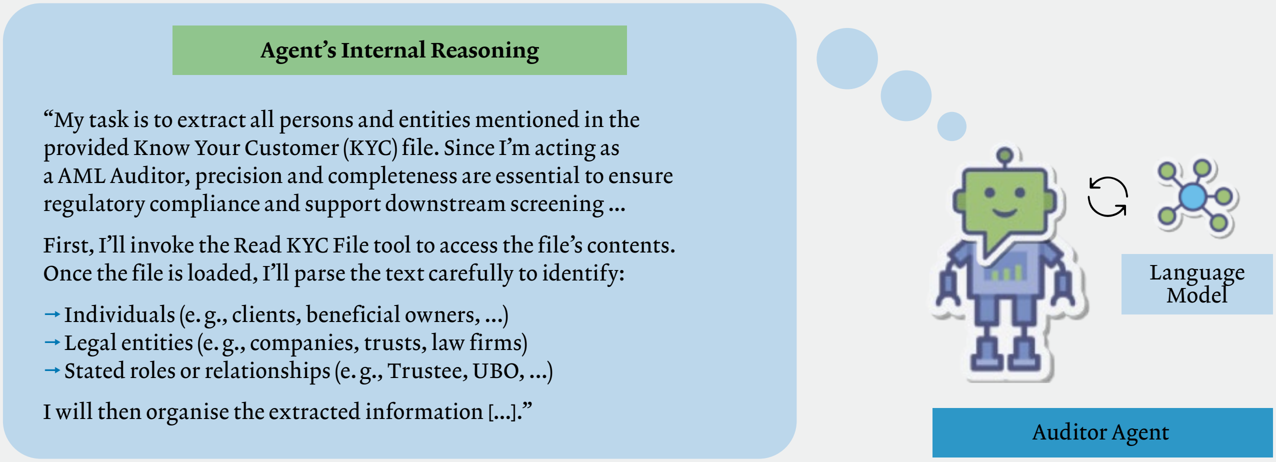
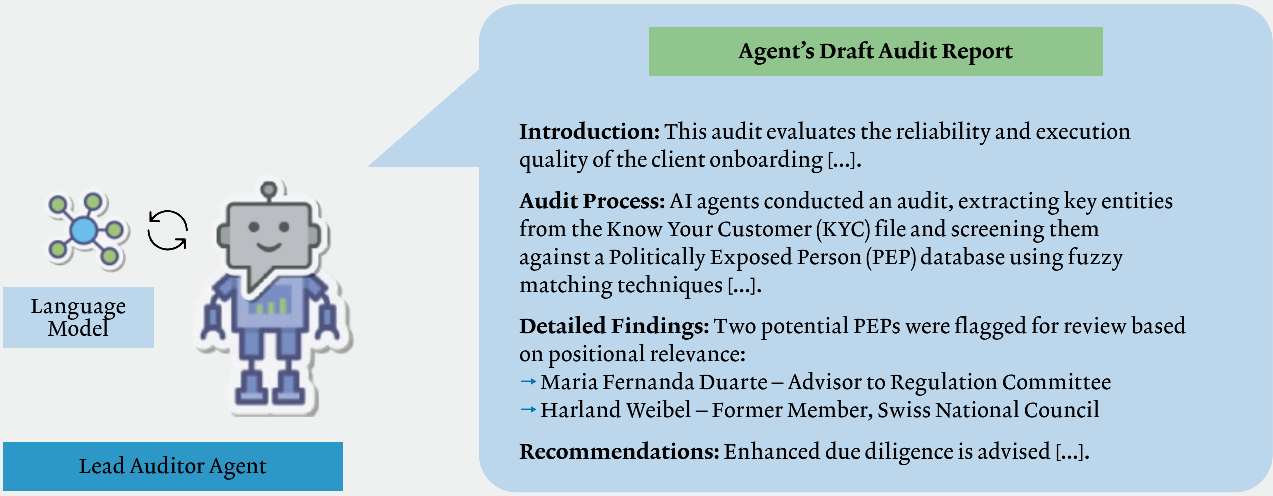


Figure 6: **AUDIT REPORT EXCERPT BY THE LEAD AUDITOR AGENT SUMMARISING AUDIT FINDINGS FROM AUDITOR AND IT AUDITOR AGENTS**



their roles or relationships. This ensured that complex client structures were distilled into a structured data format that could be effectively used for further screening.
2. *IT Auditor Agent:* Using the extracted information provided by the Auditor, this agent formulated and executed queries against a PEP database using fuzzy matching techniques. This step ensured precise and practical risk screening focused on compliance with AML and KYC regulations.
3. *Lead Auditor Agent:* This agent created an audit report based on the IT auditor's PEP screening results. Emulating a seasoned audit professional, this agent distilled the findings into clear, actionable insights supporting risk-based decision-making in client onboarding.

The agents collaborate autonomously, analysing the KYC files, querying PEP databases, performing fuzzy matching, and flagging potential findings. The agentic workflow was established using the open-source CrewAI framework, with each agent building upon the output of the previous one, as illustrated in *Figure 4*. The structured interaction between the agents ensured a streamlined audit workflow.

Each agent was equipped with MetaIAI's Llama 3 [44], a 70-billion-parameter LLM. The reasoning processes of individual agents and their inter-agent communication are conducted in natural language (as shown in *Figure 5*) to facilitate human oversight. The AI agents

1. extracted individuals and entities from a KYC file;
2. conducted fuzzy matching against a PEP database,
3. and generated a structured screening report.

An excerpt of the audit report is presented in *Figure 6*.

The case study demonstrates how integrated AI agents can perform end-to-end audit procedures to audit the effectiveness of controls in the KYC process.

4. CONCLUSION AND OUTLOOK

Advancements in agentic AI are reshaping internal auditing, with AI agents that execute complex audit tasks autonomously. Recent developments by OpenAI and Microsoft signal a growing commitment to making AI agents more interoperable through interfaces, such as the Model Context Protocol [45]. The recent release of OpenAI's Agent Software Development Kit lowers barriers to integrating AI agents into audit procedures [46]. AI agents point toward a future in which agentic collaboration mirrors the dynamics of human audit teams, integrating new levels of automation in internal auditing [47].

In parallel, the effective integration of AI agents requires auditors to cultivate a technical proficiency in developing, managing, and applying these technologies in alignment with audit objectives and regulatory requirements [48]. Additionally, interdisciplinary collaboration is essential to foster interactions between AI agents and human auditors across various domains and ensure comprehensive audit outcomes. Continuous learning remains a cornerstone for adopting innovative solutions and utilising the increasing capabilities.

The advancements in Agentic AI present unique control, oversight, and ethical challenges [49], underscoring the importance of well-defined governance structures [50]. They require appropriate oversight as human auditors are critical in validating AI-generated insights and ensuring compliance with ethical principles [51]. Structured oversight, clear operational guidelines, and continuous validation mechanisms are essential for maintaining AI agents' audit effectiveness and preserving trust.

According to the GIAS, internal auditing strengthens organisations by improving governance, risk management, and control processes. As agentic AI evolves, it offers valuable support in executing complex audit tasks. Integrating agentic AI into the audit process reinforces the relevance of internal auditing in an increasingly digital and data-driven environment. ■

Notes: 1) Bommasani, R., Hudson, D.A., Adeli, E., Altman, R., Arora, S., von Arx,S., Bernstein, M.S., Bohg, J., Bosselut, A., Brunskill, E., & others. (2021), On the Opportunities and Risks of Foundation Models. arXiv Preprint arXiv:2108.07258. **2)** Vasarhelyi, M.A., Moffitt, K.C., Stewart, T., & Sunderland, D. (2023), Large Language Models: An Emerging Technology in Accounting. Journal of Emerging Technologies in Accounting, 20(2), 1–10. **3)** Yee, L., Chui, M., and Roberts, R., with Xu, S., Why Agents are the next Frontier of Generative AI, McKinsey Quarterly (July 24, 2024), https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/why-agents-are-the-next-frontier-of-generative-ai. **4)** Heikkilä, M., What Are AI Agents?, MIT Technology Review (July 5, 2024), https://www.technologyreview.com/2024/07/05/1094711/what-are-ai-agents/ for synoptic comparison. **5)** Gu, H., Schreyer, M., Moffitt, K., & Vasarhelyi, M. (2024), Artificial Intelligence Co-Piloted Auditing. International Journal of Accounting Information Systems, 54, 100698. **6)** Kolt, N. (2024). Governing AI Agents. Social Science Research Network (SSRN). https://doi.org/10.2139/ssrn.4772956. **7)** Masterman, T., Besen, S., Sawtell, M., & Chao, A. (2024), The Landscape of Emerging AI Agent Architectures for Reasoning, Planning, and Tool Calling: A Survey. arXiv Preprint arXiv:2404.11584. **8)** Kapoor, S., Stroebl, B., Siegel, Z.S., Nadgir, N., & Narayanan, A. (2024), AI Agents That Matter. arXiv Preprint arXiv:2407.01502. **9)** Reed, S., Zolna, K., Parisotto, E., Colmenarejo, S.G., Novikov, A., Barth-Maron, G., Gimenez, M., Sulsky, Y., Kay, J., Springenberg, J.T., & others. (2022), A Generalist Agent. arXiv Preprint arXiv:2205.06175. **10)** AutoGPT an accessible AI for everyone, to use and to build on (March 30, 2023), Significant-Gravitas, https://news.agpt.co/ and https://github.com/Significant-Gravitas/AutoGPT. **11)** Anthrophic, Introducing computer use, a new Claude 3.5 Sonnet, and Claude 3.5 Haiku (October 22, 2024), https://www.anthropic.com/news/3-5-models-and-computer-use. **12)** Wu, S., Introducing Devin, the first AI software engineer (March 12, 2024), Cognition AI, https://www.cognition.ai/blog/introducing-devin. **13)** Anthropic, Introducing the Model Context Protocol (November 25, 2024), https://www.anthropic.com/news/model-context-protocol. **14)** OpenAI, Introducing Operator (January 23, 2025), https://openai.com/index/introducing-operator/. **15)** ManusAI, Leave it to Manus (March 6, 2025), https://manus.im. **16)** Gartner, Predicts 2024: The Future of Generative AI Technologies (February 28, 2024), https://www.gartner.com/en/documents/5236863. **17)** Schreyer, M., Gu, H., Moffitt, K., & Vasarhelyi, M.A. (2024), Artificial Intelligence Agentic Auditing. Available at SSRN 4909147. **18)** Gu, H., Schreyer, M., Moffitt, K., & Vasarhelyi, M. (2024), Artificial Intelligence Co-piloted Auditing. International Journal of Accounting Information Systems, 54, 100698. **19)** Ferber, J. (1995). Multi-Agent Systems, An Introduction to Distributed Artificial Intelligence. **20)** Russell, S., & Norvig, P. (2021), Artificial Intelligence: A Modern Approach, Global Edition. Pearson Higher Ed. **21)** Mei, K., Li, Z., Xu, S., Ye, R., Ge, Y., & Zhang, Y. (2024). LLM Agent Operating System. arXiv Preprint arXiv:2403.16971. **22)** Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F.L., & McGrew, B. (2023), GPT-4 Technical Report. arXiv Preprint arXiv:2303.08774. **23)** Touvron, H., Lavril, T., Izacard, G., Martinet, X., Lachaux, M.-A., Lacroix, T., & Lample, G. (2023), Llama: Open and Efficient Foundation Language Models. arXiv Preprint arXiv:2302.13971. **24)** Jiang, A.Q., Sablayrolles, A., Roux, A., Mensch, A., Savary, B., Bamford, C., & Sayed, W.E. (2024), Mixtral of Experts. arXiv Preprint arXiv:2401.04088. **25)** Burtsev, M., Reeves, M., & Job, A. (2024), The Working Limitations of Large Language Models. MIT Sloan Management Review, 65(2), 8–10. **26)** NVIDIA. (2025, March 30). AI Agents. NVIDIA Glossary. https://www.nvidia.com/en-us/glossary/ai-agents/. **27)** Schreyer, M., Gu, H., Moffitt, K., & Vasarhelyi, M.A. (2024), Artificial Intelligence Agentic Auditing. Social Science Research Network (SSRN). **28)** Huang, X., Liu, W., Chen, X., Wang, X., Wang, H., Lian, D., & Chen, E. (2024), Understanding the Planning of LLM Agents: A Survey. arXiv Preprint arXiv:2402.02716. **29)** Wei, J., Bosma, M., Zhao, V.Y., Guu, K., Yu, A.W., Lester, B., & Le, Q.V. (2021), Finetuned Language Models are Zero-Shot Learners. arXiv Preprint arXiv:2109.01652. **30)** Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M., Yih, W., Rocktäschel, T., & others. (2020), Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. Advances in Neural Information Processing Systems, 33, 9459–9474. **31)** Shen, Y., Song, K., Tan, X., Li, D., Lu, W., & Zhuang, Y. (2024), HuggingGPT: Solving AI Tasks with ChatGPT and its Friends in Hugging Face. Advances in Neural Information Processing Systems, 36. **32)** Schick, T., Dwivedi-Yu, J., Dessì, R., Raileanu, R., Lomeli, M.N., Hambro, E., & Scialom, T. (2024), Toolformer: Language Models can Teach Themselves to Use Tools. Advances in Neural Information Processing Systems, 36. **33)** Eulerich, M., Sanatizadeh, A., Vakilzadeh, H., & Wood, D.A. (2024), Is it All Hype? ChatGPT's Performance and Disruptive Potential in the Accounting and Auditing Industries. Review of Accounting Studies. **34)** Russell, S., & Norvig, P. (2021), Artificial Intelligence: A Modern Approach, Global Edition. Pearson Higher Ed. **35)** Pounds, E. (2024, October 22), What is Agentic AI? NVIDIA Blog. https://blogs.nvidia.com/blog/what-is-agentic-ai/. **36)** Ng, A. (2023, June 15). AI Agentic Workflows And Their Potential For Driving AI Progress [Video]. YouTube. https://www.youtube.com/watch?v=q1XFm21I-VQ. **37)** Institute of Internal Auditors (2025, March 20). About Internal Audit [Website]. https://www.theiia.org/en/about-us/about-internal-audit. **38)** Principle 13 Plan Engagements Effectively, The Institute of Internal Auditors. (2024). Global Internal Audit Standards. The Institute of Internal Auditors. **39)** Principle 14 Conduct Engagement Work, The Institute of Internal Auditors. (2024), Global Internal Audit Standards, The Institute of Internal Auditors. **40)** Principle 15 Communicate Engagement Results and Monitor Action Plans, The Institute of Internal Auditors. (2024). Global Internal Audit Standards. The Institute of Internal Auditors. **41)** https://github.com/GitiHubi/AgenticAuditing. **42)** Schreyer, M., Gu, H., Moffitt, K., & Vasarhelyi, M.A. (2024), Artificial Intelligence Agentic Auditing. Social Science Research Network (SSRN). **43)** Schreyer, M., Gu, H., Moffitt, K., & Vasarhelyi, M.A. (2024). Artificial Intelligence Agentic Auditing. Available at SSRN 4909147. **44)** MetaAI. (2024). Introducing MetaAI, Meta Llama 3: The most capable openly available LLM to date. Retrieved August 2, 2024, from https://ai.meta.com/blog/meta-llama-3/. **45)** Desai, Z., Introducing Model Context Protocol (MCP) in Copilot Studio (March 19, 2025), https://www.microsoft.com/en-us/microsoft-copilot/blog/copilot-studio/introducing-model-context-protocol-mcp-in-copilot-studio-simplified-integration-with-ai-apps-and-agents/. **46)** OpenAI, New Tools For Building Agents (March 11, 2025), https://openai.com/index/new-tools-for-building-agents/. **47)** Kopp, C., Schreyer, M., & Birk, M. (2024), Agentische Künstliche Intelligenz in der Wirtschaftsprüfung. WPg – Die Wirtschaftsprüfung. IDW Verlag, Düsseldorf, Germany. (in press). **48)** Tamayo, J., Doumi, L., Goel, S., Kovács-Ondrejkovic, O., & Sadun, R. (2023), Reskilling in the Age of AI. Harvard Business Review, 101(5), pp. 56–65. **49)** Shavit, Y., Agarwal, S., Brundage, M., Adler, S., O'Keefe, C., Campbell, R., Lee, T., Mishkin, P., Eloundou, T., Hickey, A., & others. (2023), Practices for Governing Agentic AI Systems. Research Paper, OpenAI. **50)** Emett, S.A., Eulerich, M., Pikoos, J., & Wood, D.A. (2024), Generative AI governance framework (Version 1.0). Connor Group. **51)** Council of Europe. (2024), Framework Convention on Artificial Intelligence.