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REVIEW

Adoption of artificial intelligence technologies in Argentina external auditing

Adopción de tecnologías de inteligencia artificial en la auditoría externa Argentina

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ABSTRACT

This study analyzes the adoption of artificial intelligence (AI) technologies in external auditing in Argentina, within a context where these tools promise to optimize processes and enhance the quality of professional judgment. Despite a high level of awareness regarding AI, its practical application remains limited and uneven. The objective was to analyze the adoption of artificial intelligence technologies in external auditing in Argentina. A mixed-methods approach with a descriptive design was employed. A total of 236 certified public accountants were surveyed between August 2024 and February 2025, and the quantitative findings were complemented by semi-structured interviews. The results show that although 97 % of respondents are familiar with the concept of AI, only 12 % apply it in their auditing work. The main barriers identified were the lack of specialized training, limited technical skills, and organizational resistance to change. Among the most valued benefits are time savings, increased accuracy, and improved detection of irregularities. The analysis allowed for the identification of three user profiles: young innovators, neutral professionals, and older individuals willing to adopt but lacking training. The study concludes that promoting targeted training programs, clear regulatory frameworks, and an innovation-oriented organizational culture is essential to bridge the gap between technological discourse and its effective implementation.

Keywords: Artificial Intelligence; External Auditing; Professional Transformation; Technology Adoption.

RESUMEN

Este estudio analiza la adopción de tecnologías de inteligencia artificial (IA) en la auditoría externa argentina, en un contexto donde estas herramientas prometen optimizar procesos y mejorar la calidad del dictamen profesional. A pesar del alto nivel de conocimiento sobre IA, su aplicación práctica aún es limitada y desigual. El objetivo fue analizar la adopción de tecnologías de inteligencia artificial en la auditoría externa en Argentina. Se empleó un enfoque metodológico mixto con diseño descriptivo. Se encuestó a 236 contadores públicos entre agosto de 2024 y febrero de 2025, complementando el relevamiento con entrevistas semiestructuradas. Los resultados revelan que, aunque el 97 % conoce el concepto de IA, solo el 12 % la aplica en su labor. Las principales barreras identificadas fueron la falta de formación especializada, la escasa capacitación técnica y la resistencia al cambio. Entre los beneficios más valorados se destacan el ahorro de tiempo, la mayor precisión y la detección de irregularidades. El análisis permitió definir tres perfiles de adopción: jóvenes innovadores, profesionales neutrales y mayores dispuestos sin formación. Se concluye que es necesario promover políticas de formación, marcos regulatorios claros y una cultura organizacional pro innovación para cerrar la brecha entre el discurso tecnológico y su implementación efectiva.

Palabras clave: Inteligencia Artificial; Auditoria Externa; Transformación Profesional; Adopción Tecnológica.

INTRODUCTION

Literature review

Artificial Intelligence

Artificial intelligence (AI) is conceived as a set of techniques and systems capable of emulating human cognitive processes, such as machine learning, natural language processing, and predictive analytics.[1] These capabilities allow machines to interpret external data, learn from it, and execute complex tasks without explicit programming for each case, which distinguishes them from traditional automation applications.[2] In business, AI is associated with achieving optimal results, where the technological "rocket" is *machine learning* and the "fuel" is *big data, and* with designing strategies that integrate its economic, functional, and ethical potential.[1,2]

Throughout the 20th century, the discipline gained its entity with milestones such as the Dartmouth conference in 1956, the AI winters, and successive revivals driven by advances in algorithms, computational power, and data availability.[3] In recent decades, the shift from symbolic approaches to connectionist models - intense neural networks - has marked a new paradigm, catalyzed by practical applications in computer vision, PLN, and intelligent process automation.[4,5]

In the field of auditing, AI has emerged as a transformative factor, enabling everything from the analysis of large volumes of transactions to the generation of real-time *insights* that improve the detection of risks and irregularities.[6,7] Recent reviews show that, by combining *machine learning* techniques with robotic process automation (RPA), it is possible to provide an audit with comprehensive coverage and continuous procedures, reducing reliance on sampling and strengthening data-driven control.[8] However, its adoption is held back by training limitations, ethical challenges, and the need for regulatory frameworks adapted to the new analytical era.[9]

Acceptance and use models

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al.[10], has established itself as a framework for investigating the adoption of AI systems in organizational contexts. According to UTAUT, individuals' intention to use a technology is determined by four key constructs:

- Expected performance (expectation that the technology will improve work outcomes),
- Expected effort (perceived ease of use),
- Social influence (perception that important people consider that the technology should be used), and
- Facilitating conditions (technical and organizational infrastructure that supports use).

Performance expectancy refers to the degree to which a user believes that AI will improve their work effectiveness; effort expectancy, to the perceived ease of employing such tools; social influence, to the degree of pressure or support exerted by other relevant individuals for their adoption; and facilitating conditions, to the technical and organizational infrastructure that supports the continued use of AI. Together, these constructs enable the diagnosis of both incentives and perceived barriers, guiding actions to maximize the acceptance and sustained use of technology within the audit firm.

Beyond UTAUT, some authors have developed specific conceptual frameworks for AI business strategy. Caner and Bhatti[1] articulate a model that consolidates technical and business views, identifying five fundamental elements: AI capabilities and limitations, AI economics, organizational functions, workforce, and regulatory and ethical considerations. By integrating both individual adoption determinants and strategic and regulatory requirements, these approaches complement the UTAUT, providing a holistic view for successfully planning and implementing AI-based audit projects.

External audit and digital technologies

The external audit process has undergone a profound transformation thanks to the incorporation of digital technologies, which enable the transition from one-off reviews to continuous audits based on the analysis of large volumes of data. *Big Data* and *data analytics* tools allow the sampling of 100 % of transactions, the automatic identification of *outliers,* and the generation of real-time risk indicators, which significantly optimize resources and improve the quality of audit conclusions.[8] Likewise, the adoption of machine learning techniques and robotic automation of processes has boosted the detection of irregularities and efficiency in repetitive tasks, freeing auditors to focus on professional judgment and exception analysis.[11]

Despite these benefits, the implementation of digital technologies in external audit faces significant challenges stemming from cybersecurity, the integrity of digital evidence, and the lack of regulatory frameworks adapted to the analytics era. Industry reports emphasize the need to enhance training in new tools and establish clear policies for the ethical use of AI, thereby mitigating algorithmic biases and ensuring the transparency of automated decisions.[12] In addition, auditors must adapt their risk assessment methodologies to incorporate

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predictive analytics models, following guidelines such as those proposed by Asif Qureshi.[7]

Motivation

External auditing is at a turning point with the deployment of tools such as robotic automation of processes, analysis of large volumes of data and artificial intelligence, which promise to optimize procedures, expand the coverage of tests and improve the detection of irregularities; however, their practical application is still limited by gaps in specialized training, cultural resistance in firms and regulatory gaps that generate risks of bias and compromise the quality of the opinion. This tension between opportunities and barriers drives the need to create local empirical evidence that quantifies the level of knowledge, reveals concrete cases of use, and explores the perception of Argentine accounting professionals of these emerging technologies. Throughout this research, the guiding question is: How are artificial intelligence technologies adopted in external auditing in Argentina, and what level of knowledge, use cases, benefits, and barriers are perceived by accounting professionals that explain their degree of effective implementation?

Research objectives

The general objective of this research is to analyze the adoption of artificial intelligence technologies in external auditing in Argentina; to this end, the specific objectives are: (i) to determine the level of knowledge and familiarity of accounting professionals with these technologies, (ii) to identify the specific use cases and degree of implementation of AI in their external auditing practices, and (iii) to evaluate the perceived benefits and barriers that influence their effective incorporation Computer systems.

METHOD

Study approach and design

The methodological design adopted was descriptive, with a mixed approach that combined quantitative and qualitative strategies to obtain a comprehensive view of the phenomenon under investigation: the adoption of AI technologies in external auditing and the factors that motivate or hinder their use by practitioners. This approach was appropriate to address an emerging topic, characterized by its novelty, complexity, and scarcity of previous empirical research in the Latin American context.

The research was conducted in Argentina between August 2024 and February 2025. The context was marked by a growing adoption of advanced digital technologies in the accounting sector, although with significant asymmetries in terms of technological infrastructure and professional capabilities between large and small firms. These conditions provided fertile ground for exploring the perceptions, knowledge, and experiences of external auditors vis-à-vis the adoption of AI in their professional practice.

Population and sample

The target population of the study consisted of accounting professionals registered in Argentina who work in external audit-related functions, including both large firms and small and medium-sized firms. A non-probabilistic purposive sampling method was used, targeting professionals with experience or knowledge in auditing processes. Data collection took place between August 2024 and February 2025, yielding a total of 236 valid responses. Participants included practicing external auditors, partners, and managers of audit firms, as well as independent professionals, distributed in different regions of the country. The data were analyzed using descriptive statistical techniques (frequencies, percentages, and simple crosstabs by age, type of firm, and level of experience), complemented with a Multiple Correspondence Factor Analysis (MCA) to identify profiles and patterns of technological adoption. Interviews with 10 audit managers from large audit firms (*Big Four*) were also incorporated.

Collection instruments

To determine the level of knowledge and familiarity with AI technologies among external audit professionals, a structured survey was designed to obtain quantifiable data on this aspect. The instrument was validated by experts in auditing and emerging technologies, who evaluated its clarity, relevance, and consistency with the research objectives. The instrument included closed multiple-choice questions and open-ended questions aimed at measuring the degree of knowledge, previous experience, level of technological training, and willingness to be trained in AI tools. The survey was distributed using digital forms through professional networks and academic institutional channels.

Data analysis procedures

Data collection allowed the development of a robust statistical analysis that included univariate, bivariate, and multivariate techniques. In the univariate stage, frequencies and percentages were analyzed to describe sociodemographic variables (age, years of professional practice, experience in *Big Four* firms), as well as aspects

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related to the knowledge, use, and perception of artificial intelligence (AI) in auditing. This first approach made it possible to establish general patterns on the degree of familiarity, current uses, and perceived barriers to technological adoption.

Subsequently, bivariate analyses were conducted to explore relationships between variables, such as the relationship between seniority in the profession and the effective use of AI, or the relationship between the type of firm and the level of training received. Finally, a multiple correspondence factor analysis (MCA) was applied to identify distinct profiles among participants based on their responses.

This multivariate technique enabled the application of a hierarchical classification, segmenting the professionals into three clusters with distinct characteristics in terms of age, experience, level of training, and attitude towards AI. This comprehensive statistical analysis methodology was essential to understand not only the individual levels of adoption but also the dynamics and structural determinants that influence the implementation of emerging technologies in the professional practice of external auditing.

RESULTS

Level of knowledge and familiarity with AI

The results indicate a high level of knowledge of artificial intelligence among external audit professionals, with 97 % of respondents stating that they are familiar with the concept and its basic applications in the accounting field. However, this familiarity typically results from theoretical or high-level knowledge acquired primarily through specialized readings, seminars, and industry conferences, rather than from practical experience.

Moreover, although there is almost unanimous acceptance of the relevance of AI, as reflected in the high recognition rate, only 12 % of respondents have incorporated AI-based tools into their ex-officio audit procedures. These professionals, mostly young and with complementary training in digital technologies, have conducted pilots or proofs of concept that illustrate benefits such as time savings and improved detection of irregularities. However, the majority group is in an “observer” or “evaluator” phase, pending more structured training and access to real application environments in their firms in order to make the leap from theory to practice.

Perceived barriers and facilitators

Respondents mainly identified three barriers to the adoption of AI in external audit. First, the lack of specialized training emerges as the most critical barrier: only 12 % of practitioners reported having applied IA in their work, which is related to educational gaps in both university and in-firm continuing education. Secondly, the limited technical training available prevents auditors from feeling comfortable operating advanced machine learning or big data processing tools. Finally, resistance to cultural change persists, especially among middle-aged and older professionals, who tend to rely more on traditional methodologies and are reluctant to delegate professional judgment tasks to algorithms.

As a counterpoint, auditors recognize several factors that facilitate the integration of AI into their processes. The perception of significant time savings in document sampling and analysis routines, along with improved detection of irregularities thanks to the ability of algorithms to scan large volumes of data, stands out as the main incentive. In addition, they valued the increased accuracy of the results, by reducing the probability of human error in repetitive calculations. From the multivariate analysis, a profile of “young and trained professionals” was detected who have already incorporated AI in their audits, acting as change agents and role models within their teams.

Adoption profiles

The classification analysis revealed three distinct profiles in terms of AI adoption in external auditing. The first profile group consists of young professionals with recent training in digital technologies and a high predisposition to experiment with AI tools; they usually have participated in pilot projects or integrated predictive analytics algorithms into their procedures (“innovative” profile). The second group consists of middle-aged professionals with solid experience in traditional auditing, but without specific training in AI. They exhibit a neutral attitude - neither enthusiastic nor reluctant - and are waiting for more conclusive results before incorporating the technology (“observer” profile). The third group is made up of older professionals with little or no training in AI, although with a favorable disposition and curiosity to understand its applications; they depend on external training and institutional pressure to leap from theory to practice (“apprentice” profile).

These adoption profiles have direct implications for the AI implementation strategy in audit firms. For the innovator profile, it is sufficient to offer pilot platforms and advanced use cases that allow them to scale their projects. For the observer profile, it is key to generate concrete evidence of time savings and improved risk detection through demonstration workshops and the dissemination of “*quick wins*”.

The results of the multivariate analysis that allows observing the *clusters* are shared below:

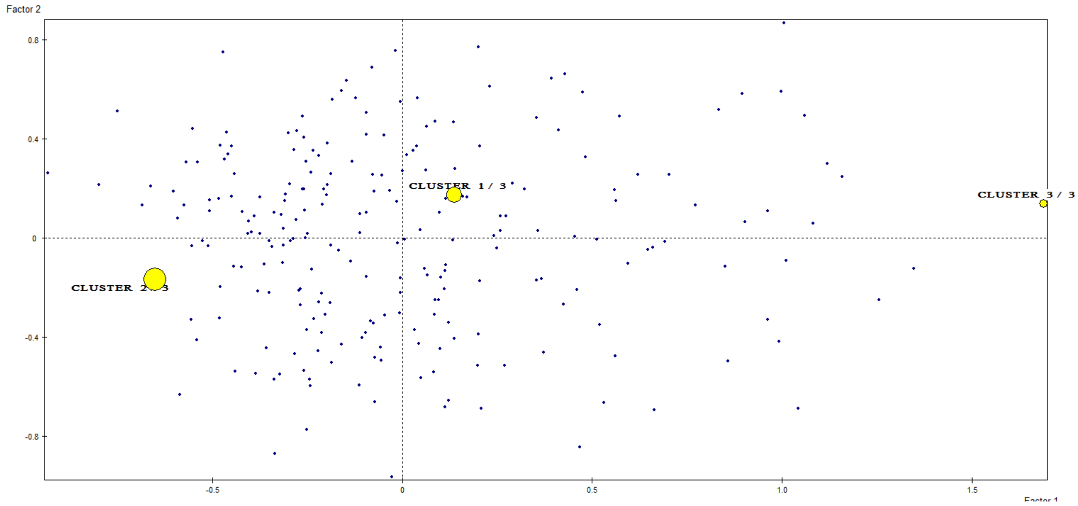

Figure 1. Classification of observations (SpadWin5.6)

Group: CLUSTER 1 / 3 (Count: 82 - Percentage: 34.75)							
Variable label	**Caracteristic categories**	**% of category in group**	**% of category in set**	**% of group in category**	**Test-value**	**Probability**	**Weight**
POSI	Circularización e información	36,59	19,49	65,22	4,56	0,000	46
POSI	Análisis de datos	28,05	14,41	67,65	4,06	0,000	34
BARR	Falta de conocimiento sobre la tecnolo	47,56	30,93	53,42	3,84	0,000	73
MOTI	Mejorar la eficiencia de los procesos In	68,29	53,81	44,09	3,14	0,001	127
NEGA	Inspección física de activo	15,85	7,63	72,22	3,13	0,001	18
FORM	No	97,56	89,41	37,91	2,97	0,001	211
NEGA	Análisis de saldos	12,20	5,51	76,92	2,91	0,002	13
EDAD	55 años o mas	13,41	6,36	73,33	2,89	0,002	15
IAPP	Detección de fraudes Procesamiento d	8,54	3,39	87,50	2,76	0,003	8
IAVT	Ahorro de tiempo en la realización de	8,54	3,39	87,50	2,76	0,003	8
NEGA	Ninguna	6,10	2,12	100,00	2,60	0,005	5
IAPP	Herramientas de análisis predictivo De	7,32	2,97	85,71	2,42	0,008	7
IAFU	Análisis de datosAutomatización de ta	8,54	3,81	77,78	2,35	0,009	9

Figure 2. Cluster 1/3 - "Innovative" profile

Group: CLUSTER 2 / 3 (Count: 116 - Percentage: 49.15)							
Variable label	**Caracteristic categories**	**% of category in group**	**% of category in set**	**% of group in category**	**Test-value**	**Probability**	**Weight**
NEGA	No responde	68,97	43,22	78,43	7,90	0,000	102
POSI	NS/NC	53,45	30,93	84,93	7,46	0,000	73
IAPP	No conozco aplicaciones específicas	75,86	53,39	69,84	6,79	0,000	126
IAAU	No	100,00	87,71	56,04	6,12	0,000	207
IAOT	No	92,24	75,85	59,78	5,83	0,000	179
IAFU	No utilizo IA	56,90	42,80	65,35	4,20	0,000	101
AUEX	No	63,79	49,58	63,25	4,19	0,000	117
BIG4	No	92,24	82,63	54,87	3,74	0,000	195
MOTI	Reducir el tiempo dedicado a tareas re	31,03	20,76	73,47	3,71	0,000	49
FORM	No	96,55	89,41	53,08	3,41	0,000	211
TITU	Mas de 10 años	16,38	9,75	82,61	3,25	0,001	23
COMI	No responde	91,38	83,05	54,08	3,23	0,001	196
IADS	Riesgo de errores en la programación d	24,14	16,95	70,00	2,74	0,003	40
IAVT	Ahorro de tiempo en la realización de	12,93	8,05	78,95	2,51	0,006	19
EDAD	45 - 54 años	9,48	5,51	84,62	2,41	0,008	13
EDAD	45-54 años	29,31	22,46	64,15	2,33	0,010	53

Fiure 3. Cluster 2/3 - "Observer" profile

Group: CLUSTER 3 / 3 (Count: 38 - Percentage: 16.10)							
Variable label	**Caracteristic categories**	**% of category in group**	**% of category in set**	**% of group in category**	**Test-value**	**Probability**	**Weight**
IAOT	Si	84,21	24,15	56,14	8,60	0,000	57
IAAU	Si	60,53	12,29	79,31	8,22	0,000	29
FORM	Si	50,00	10,59	76,00	7,07	0,000	25
BIG4	Si	47,37	17,37	43,90	4,64	0,000	41
AUEX	Si	81,58	50,42	26,05	4,13	0,000	119
IAPP	Software de automatización de audito	23,68	6,36	60,00	3,80	0,000	15
IAPP	Procesamiento de grandes volúmenes	31,58	13,14	38,71	3,13	0,001	31
NEGA	Pericias de bienes	52,63	29,66	28,57	3,08	0,001	70
IAFU	Automatización de tareas rutinarias	15,79	4,24	60,00	2,96	0,002	10
EDAD	35-44 años	44,74	26,27	27,42	2,54	0,006	62
IADS	Complejidad en la implementación Fal	18,42	7,20	41,18	2,35	0,009	17

Figure 4. Cluster 3/3 - "Learner" profile

Finally, the apprentice profile requires basic training and mentoring programs, as well as clear incentives -for example, inclusion of AI usage metrics in performance evaluations- that reduce cultural resistance and consolidate the shift towards more analytical listening practices.

DISCUSSION

Interpretation of the findings

The first relevant result is the high level of theoretical knowledge about artificial intelligence among the surveyed professionals (97 %), in contrast to a low practical adoption in external auditing (12 %). This finding confirms what Mpofu[9] and Asif Qureshi[7] pointed out, who warn that the conceptual recognition of AI does not automatically translate into its operational use. The gap between knowing and doing can be attributed to the lack of specialized training, insufficient technological infrastructure, and an organizational culture still reluctant to innovation, as also highlighted by KPMG.[12] The second relevant finding is the identification of three adoption profiles: innovators, observers, and learners. This segmentation reflects the diversity of attitudes towards technology within audit firms. It aligns with the UTAUT model proposed by Venkatesh et al.[10], which suggests that performance expectation, perceived effort, and social influence have distinct impacts depending on the professional profile. In this sense, "innovators" respond positively to facilitating conditions and exhibit an active disposition. At the same time, "observers" present passive knowledge without practical integration, and "learners" show interest but lack the necessary technical competencies. These results are also in line with those proposed by Caner and Bhatti[1], who argue that an effective AI adoption strategy must consider not only the technological dimension but also human capabilities, organizational culture, and the regulatory context. Consequently, they justify the need to design strategies differentiated by profile: intensive training for "learners", leadership and incentives for "observers", and experimentation spaces for "innovators". This segmented approach would reduce entry barriers, encourage more effective appropriation of technology, and facilitate a more inclusive digital transformation in the field of external audit.

Comparison with previous studies

Our results are in agreement with Zhang[6], who noted that, despite widespread recognition of the advantages of digital tools in auditing, there are still training and technical limitations that restrict their practical application. Similarly, Mpofu[9] documented cultural resistance and ethical concerns as barriers to the use of AI in external auditing, while Caner and Bhatti[1] stressed the importance of enabling conditions (infrastructure and institutional support) for new technologies to be successfully incorporated into business strategy.

Practical and regulatory implications

At the practical level, audit firms should design modular training programs that address everything from *machine learning* fundamentals to specific use cases, for example, anomaly detection in *Big* Data, aligned with the identified adoption profiles. In addition, it is essential to integrate AI pilots into real processes, document "*quick wins*," and communicate results to all levels of the organization to generate momentum and internal legitimacy. From a regulatory perspective, oversight bodies and professional boards should update auditing standards, for example, RT 37 as amended by RT 53 in Argentina, to include guidelines on the validity of AI-generated digital evidence, transparency of algorithms, and management of risks associated with algorithmic biases.

Limitations of the study

The main limitations of this study derive from its cross-sectional design and convenience sampling among accounting professionals from firms located in Argentina, which restricts the generalizability of the results to other contexts and may have introduced self-selection biases. In addition, the measurement of AI knowledge, attitudes, and practices was based exclusively on a self-administered questionnaire and semi-structured interviews, and is therefore subject to social desirability biases and discrepancy between stated and actual behavior. The static nature of the research, limited to six months, precludes capturing the evolving dynamics of AI technologies and their emerging uses in auditing, as well as the effects of training initiatives or regulatory changes after field closure. Finally, although multivariate analysis allowed for the profiling of respondents, there were no objective performance indicators—for example, time savings or improvements in risk detection—that would allow for the empirical quantification of the real impact of AI adoption on audit quality.

CONCLUSION

This study confirms that, although there is almost unanimous recognition of the relevance of IA in external auditing, its practical adoption remains marginal and is limited by training gaps, cultural resistance, and regulatory gaps. The contrast between the high level of theoretical familiarity and the low actual use of AI tools reveals that the availability of information does not translate directly into operational transformation. The identification of three adoption profiles (innovator, observer, and learner) highlights the need for differentiated strategies: some are already experimenting with AI pilots, while others, although receptive, demand concrete evidence of benefits; and a third group requires basic training and institutional support.

Overcoming the gap between knowledge and practice of IA in auditing requires a comprehensive approach that combines training, empirical evidence, and regulatory adaptation. Only in this way will firms be able to transform their processes, maximize the value of data, and maintain user confidence in an increasingly digitized environment.

In terms of practice recommendations, and to accelerate the effective incorporation of AI, audit firms should design training programs tailored to each profile: advanced training and pilot projects for innovators, demonstration workshops and dissemination of "*quick wins*" for observers, and introductory courses with mentoring for trainees. It is also vital to systematically document and communicate success stories (such as time savings, increased test coverage, and anomaly detection) to legitimize the cultural change. At the institutional level, it is advisable to update auditing standards, for example, by incorporating criteria on digital evidence and the transparency of algorithms in the modified RT 37, and to foster collaborations with AI solution providers to ensure compatibility and governance of new tools.

It is suggested to deepen longitudinal studies that measure the real impact of AI on the efficiency and quality of the ruling -for example, comparing error metrics, execution time and irregularity detection before and after implementation-, as well as to extend the analysis to international contexts to assess how cultural and regulatory factors influence adoption. It would also be helpful to explore advanced use cases in sub-areas of auditing (e.g., forensic analysis, continuous auditing) and to study algorithmic risk assessment methodologies, thereby developing internal control frameworks tailored to hybrid human-machine environments.

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CONFLICT OF INTEREST

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Formal analysis: Juan Ignacio Ruiz.
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Methodology: Verónica Olocco, Alfredo Baronio.
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