Strategies And Conflicts Between Actors In The Use Of Machine Learning Tools To Improve Accounting Management And Organizational Growth

David Antonio Franco Borré[1] , Raúl José Martelo Gómez[2] , Pedro Juan Guerrero Muñoz[3]

Abstract

The digitalization of accounting processes, assisted by machine learning, has changed the way financial management is performed. Although its use creates tensions and specific dynamics among the actors involved, it impacts the way strategic decision-making processes are carried out. This article studies the strategic relations in the use of this tool through the MACTOR methodology. The results show that certain actors drive digital transformation, while others respond and adapt to decisions made by dominant actors. At the same time, strong convergences are evident among those actors who favor automation and efficiency, but divergences are also identified with those who declare themselves advocates of regulation and job preservation. In this sense, a strategic use that takes into account greater efficiency, regulation, and the adaptation of human talent is necessary.

keywords: Machine Learning, MACTOR, digitalization, management, organizational growth.

Introduction

The evolution of Artificial Intelligence (AI) and Machine Learning (ML) technologies has had a significant impact on the fields of application in which they are used, particularly in accounting and organizational management (Hasan, 2021). These technologies facilitate process automation, increase the accuracy of accounting forecasts, and optimize strategic decision-making in accounting practice (Chakri et al., 2023). From the digitalization of accounting to the use of intelligent algorithms, they have boosted the practice of real-time big data analysis. This development is one of the main reasons why this field has taken the leap toward change in management and its development (Ranta et al., 2023).

Along these lines, tools such as ContaWeb-BI, a platform derived from a joint project developed by the University of Cartagena and Colciencias, appear to represent a solution for accounting management practices and strategic decision-making, given that they allow for advanced use of ML algorithms to detect trends and identify financial risks. However, the integration of these technologies is not without its challenges, given that it faces interaction conflicts between different actors within organizations, such as accountants, financial analysts, or managers (Tuzcuoğlu, 2023).

The literature on ML in accounting emphasizes its impact on the quality of accounting information (improving the accuracy of financial reports), optimizing costs, and reducing the risk of fraud (Bertomeu et al., 2021). Recent studies analyze the automation of accounting supported by ML algorithms to improve the operational efficiency and the competitiveness of companies in the market (Ding et al., 2020). In particular, Ranta et al. (2023) focus on how the use of ML techniques has led to new ways of assessing financial risks and financial planning, while Van den Bogaerd and Aerts (2011) analyzed how the use of ML in managerial accounting has transformed the way large volumes of accounting data are analyzed and processed.

Despite advances in the implementation of ML initiatives in accounting management, the adoption of these types of tools by organizations causes some conflicts and organizational problems. Discrepancies between different actors, such as accountants, managers, and technology developers, can generate obstacles in the implementation of this technology as a tool for decision-making (Lei et al., 2022). One of the problems that arises is the resistance to change and the limited technical knowledge of accounting professionals when it comes to adopting the required technologies (Cai et al., 2019). The automation of certain accounting tasks, on the other hand, entails uncertainty in the redefinition of roles and commitments of the actors in the organization, which generates conflicts between them (Chae, 2024).

In this regard, the MACTOR methodology (Method, Actors, Objectives, Results, Strength) has been used in numerous strategic studies as a technique to analyze how the relation of the strength of several actors is established, in a multiplicity of sectors (Quinteros & Hamann, 2017). For example, the work developed by Bendahan et al. (2004) analyzes the interaction between several actors in technological decision-making, as well as power relations, conflicts, and alliances in a complex organizational system. Similarly, Ben-Daoud et al. (2023) applied MACTOR to analyze water resources

[1] Specialist in University Teaching. Master in Computer Science. Systems Engineer, Tenured Research Professor of the Systems Engineering Program at the Universidad de Cartagena. Leader of the GIMATICA Research Group. Cartagena de Indias, Colombia. Email: dfrancob@unicartagena.edu.co. ORCID: https://orcid.org/0000-0001-7500-0206

2 Specialist in Networks and Telecommunications; Master in Computer Science. Systems Engineer. Tenured Research Professor of the Systems Engineering Program at the Universidad de Cartagena. Leader of the INGESINFO Research Group. Cartagena de Indias, Colombia. E-mail: rmartelog1@unicartagena.edu.co
ORCID: https://orcid.org/0000-0002-4951-0752.

[3] Systems Engineer, Universidad de Cartagena; Software Developer; CVLAC: https://scienti.minciencias.gov.co/cvlac/visualizador/generarCurriculoCv.do?cod_rh=001923048; Email: pjgm181818@gmail.com

management, specifically the dynamics of actors, evidencing strategic divergences and the adequacy of policies aimed at sustainability and inclusion.

For their part, Elmsalmi and Hachicha (2014) used this methodology to align actors' strategies with their objectives and achieve greater stability and efficiency in supply chain management. In the same context, Riadh (2022) applied MACTOR in the field of tourism to measure how actors develop digital transformation strategies in tourist destinations, while Makmun et al. (2024) explained how this methodology is useful for analyzing the dominance relations between actors in the agricultural industries, in addition to providing an organized approach to the negotiation and design of cooperation strategies.

As can be seen, this technique is valid for the analysis and visualization of conflicts, agreements, and domain structures among actors in different strategic contexts. The usefulness of MACTOR in this research lies in its ability to recognize conflicts and strategies arising from the adoption of ML in accounting management. The digital transformation in accounting management affects the efficiency of business processes, the structure of organizations, and the power dynamics within organizations (Duan et al., 2023). Therefore, the objective of this study was to analyze the conflicts and strategies of actors in the use of ML tools to improve accounting management and organizational growth.

The study and analysis of these conflicts can lead to the development of strategies that improve the integration of cutting-edge technologies into accounting management and reduce resistance to such integration by different actors, in addition to promoting an innovative organizational culture (Pozo-Antúnez et al., 2021). The results obtained in this research are expected to be of interest to researchers, accounting professionals, and business managers concerned with digital transformation or the adoption of emerging technologies in financial management.

Methodology

This work is framed within qualitative research and was designed according to an exploratory-descriptive design (Herrera, 2017). The choice of qualitative research has been justified by the need to know and understand the dynamics underlying the use of ML tools applied to accounting management, as well as the conflicts and strategies of the parties involved (Ranta et al., 2023). While the exploratory design allows studying an emerging phenomenon on which there is still little research, the descriptive nature gives rise to a detailed representation of the perceptions and experiences of experts in the field (Fieberg et al., 2022).

The sample consisted of 12 experts from three different areas of expertise: managerial accounting, artificial intelligence applied to finance, and organizational management. The selection of experts was carried out through purposive sampling, taking into account their academic research experience and practical experience implementing ML in accounting and business (Bhimani, 2020). The choice of this type of experts is justified by the need to have an interdisciplinary view of the benefits and barriers of technological adoption in accounting (Liaras et al., 2024).

The research was developed as follows: first, a systematic analysis of the scientific literature on the application of ML in accounting and its effect on organizational growth was conducted. Tags such as "machine learning in management accounting" and "AI in financial management" were used to obtain relevant articles (Ranta et al., 2023). Second, based on the conclusions of the documentary review, a script of questions for the expert interviews was developed, which were recorded for subsequent analysis (Ionescu, 2022).

In order to strengthen the analysis and validity of this research, it was decided to incorporate the use of ContaWeb-BI, a comprehensive accounting and business intelligence system with advanced ML functionalities. This complemented data collection and analysis because, by managing users and companies within the platform, it helped identify strategic roles in conflicts and in the strategies associated with the adoption of ML techniques in accounting management (Chowdhury, 2023). The incorporation of ContaWeb-BI was used as a link between theoretical analysis and a tool applied in accounting management scenarios to strengthen the validity of the study.

The data obtained were analyzed using the MACTOR technique, which allows for mapping power relations, alliances, and conflicts among the agents with whom it interacts (Van den Bogaerd & Aerts, 2011). This technique was considered appropriate because it allows for identifying the strategic interests of the actors, as well as structuring the dynamics of interactions in decision-making associated with accounting management (Nielsen, 2022).

On the other hand, the study presented some limitations: first, although attempts were made to contact prominent specialists in the literature, some were unable to participate due to a lack of time or corporate confidentiality (Chowdhury, 2023). Similarly, the interpretation of qualitative data is always subject to bias, which can be mitigated through triangulation with documentary review (Ding et al., 2020). Furthermore, given that this is a qualitative study with a small number of participants, the findings may not be extrapolated to all types of organizations, but they can serve as an exploratory basis for future quantitative studies (Bertomeu, 2020).

Results

The results of this research reveal that the implementation of ML tools in accounting management generates both strategic opportunities and conflicts among the actors involved. Through analysis using the MACTOR methodology, the main actors, their strategic objectives, their strategic positions, and the power dynamics that influence the adoption of these technologies in the organizational context were identified.

Identification of key players in the adoption of machine learning in accounting

Document review and expert interviews allowed for classifying actors into three main groups: Enablers (pro-innovation), Resisters (Traditionalists), and Neutrals. Enablers promote the adoption of ML, arguing that it improves operational efficiency, optimizes decision-making, and reduces financial fraud. Resisters express concerns about the reliability of algorithms and potential job displacement, so resistance to change and lack of training in new technologies were recurring barriers. Neutral actors seek a balance between innovation and regulatory compliance.

Table 1 presents the key actors identified in the study, classified with a unique code for analysis in the MACTOR methodology. They have been grouped according to their role within the accounting system and their level of influence on the adoption of ML. Facilitating actors (A1, A2, A3) include software developers, technology companies, and business executives, who drive the adoption of tools such as ContaWeb-BI to improve efficiency in accounting management. Resistant actors (A4, A5) include traditional accountants and auditors, concerned about the reliability of AI models and the impact on their job functions. Neutral actors (A6, A7, A8) include financial managers, government regulators, and training providers.

Table 1. Actors identified in the adoption of machine learning in accounting

Code	Actor	Role within the System
A1	Software developers	They create and optimize machine learning tools for accounting.
A2	Technology companies	They promote the digitalization of accounting and financial management.
A3	Business executives	They decide on the adoption of new technologies to optimize accounting processes.
A4	Traditional accountants	They execute and supervise accounting tasks using conventional methods, demonstrating resistance to change.
A5	Auditors	They verify the validity of financial statements and question the reliability of algorithms.
A6	Financial managers	They assess the risks and benefits of adopting machine learning in financial management.
A7	Government regulators	They establish regulations and oversee the implementation of technologies in accounting.
A8	Training providers	They offer ML training to reduce the technology gap.

Source: Authors

Identification of the strategic objectives of the actors

Table 2 presents the strategic objectives of each actor identified in the study. These objectives reflect the interests, priorities, and positions of each group regarding the adoption of ML in accounting management. Pro-innovation actors seek to implement ML to improve efficiency and competitiveness. Critical or resistant actors seek to preserve their professional role and ensure transparency of financial information, and neutral actors seek to balance innovation with regulation and training.

Table 2. Strategic objectives of the actors

Code	Strategic objectives	Actor
O1	To design and implement machine learning algorithms to automate accounting and improve data processing efficiency.	Software developers
O2	To promote accounting digitalization through the development of advanced platforms such as ContaWeb-BI.	Technology companies
O3	To increase profitability and operational efficiency through the automation of accounting tasks and AI-based decision-making.	Business executives
O4	To preserve the human role in accounting, ensure proper interpretation of AI-generated data, and minimize the impact on employment.	Traditional accountants
O5	To ensure the transparency, accuracy, and reliability of financial data processed by machine learning.	Auditors
O6	To balance technological efficiency with financial security, ensuring that automation does not pose risks to financial management.	Financial managers
O7	To establish clear regulations for the use of AI in accounting, ensuring compliance with ethical and financial standards.	Government regulators
O8	To develop machine learning training programs for accountants and auditors, facilitating the technological transition.	Training providers

Source: Authors

The above information is key to constructing the matrix of strategic convergences and divergences in the MACTOR methodology, allowing the visualization of areas of cooperation and conflict between the actors.

Matrix of direct influence (MDI)

The MDI assesses the level of influence that each actor exerts on the others in relation to the adoption of machine learning in accounting management. The scale used is: 0, no influence; 1, influences the processes of others; 2, influences the projects of others; 3, influences the mission of others; 4, influences the existence of others. As can be seen in Figure 1, actor A1 influences the mission level of actor A2, influences the process levels of actors A3, A4, A5, and A6, does not influence A7, and influences the project level of actor A8. This is how the MDI is interpreted.

Figure 1. Matrix of direct influence (MDI)

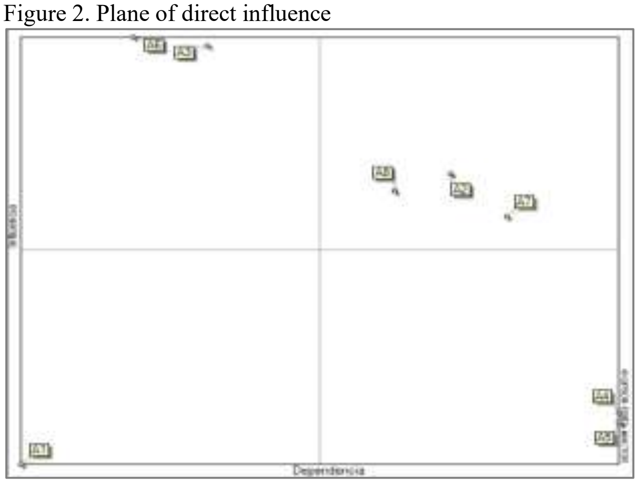
A/A	A1	A2	A3	A4	A5	A6	A7	A8
A1	0	3	1	1	1	1	0	2
A2	3	0	4	2	2	1	3	3
A3	2	4	0	3	2	4	3	3
A4	1	1	2	0	3	1	2	1
A5	0	1	1	3	0	2	4	1
A6	2	4	3	2	3	0	3	3
A7	0	3	2	3	4	2	0	3
A8	3	3	1	3	3	2	3	0

Source: Authors

Based on the results of completing the MDI, the Plane of direct influence shown in Figure 2 was drawn, which shows that the actors located in the upper left quadrant (Dominant) were actors A3 and A6; while those located in the upper right quadrant (Link) were actors A2, A7 and A8. The actor located in the lower left quadrant (Autonomous) was actor A1; and the actors located in the lower right quadrant (Dominated) were actors A4 and A5.

These results show that dominant actors (executives and financial managers) have the greatest decision-making power over ML adoption and directly affect all other actors. Link actors (regulators, technology companies, and training providers) play a crucial role in connecting dominant and dominated actors. Dominated actors (accountants and auditors) have low decision-making capacity but are highly dependent on the actions of dominant and link actors, while autonomous actors (software developers) have less participation in strategic decision-making and operate relatively independently.

Figure 2. Plane of direct influence



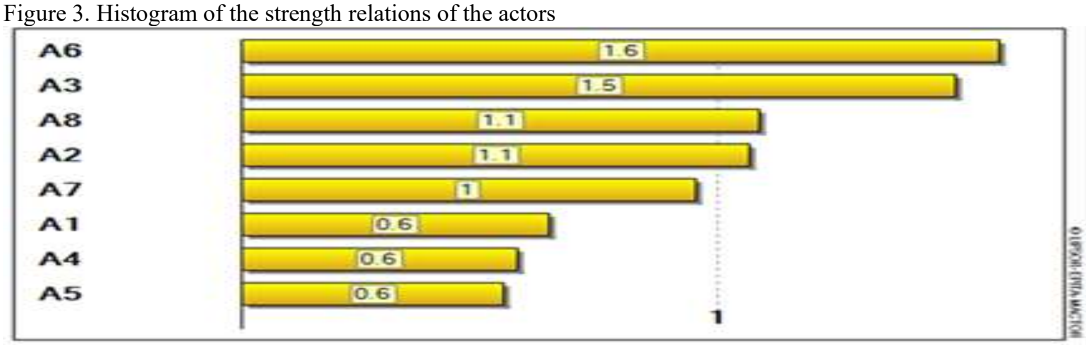
Source: Authors

In this sense, dominant actors lead the digital transformation in accounting, link actors facilitate the adaptation of dominated actors, dominated actors must receive support to avoid technological exclusion, and autonomous actors can generate innovation without being affected by regulations.

Relations of strength of each of the actors

On the other hand, when classifying the actors, an analysis of their strength relations was carried out using the histogram generated by the MACTOR software. As can be seen in Figure 3, the results indicate that the actors with the greatest power or strength, in descending order, are A6, A3, A8, and A2; A7 presents an intermediate level of strength, while A1, A4, and A5 have the least influence.

Figure 3. Histogram of the strength relations of the actors



Source: Authors

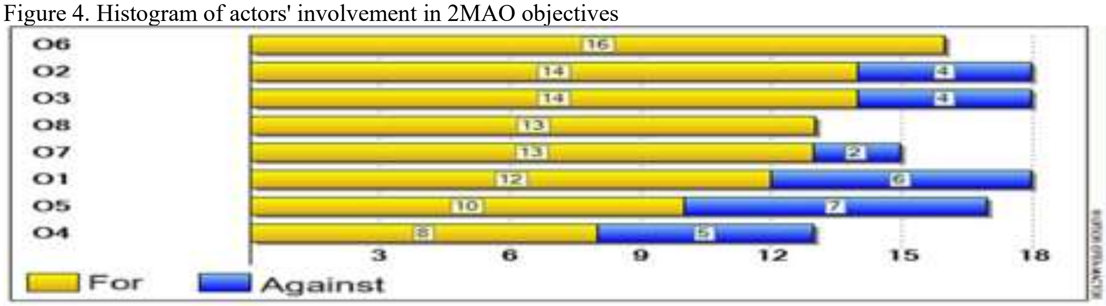
Positioning of actors with respect to objectives

With the above results, the position of the actors in relation to the objectives is examined using the histogram of actors' involvement on second-order objectives (2MAO). In Figure 4, this histogram reflects the different levels of actors' commitment to the objectives, while the histogram of involvement on third-order objectives (3MAO), represented in Figure 5, shows the actors' capacity to influence them.

The histogram analysis in Figure 4 reveals that objectives O6, O2, and O3 have a high level of acceptance among the system's actors. This suggests that they are consensual strategic objectives, with strong support for their implementation. O8 and O7 also have majority support, although with a slight level of opposition. Together, these objectives may represent strategies aligned with organizational growth and the improvement of accounting management through ML tools.

On the other hand, the objectives with the greatest opposition ("Against" in blue) were: O1, O5, and O4. Although most actors support O1, the high level of opposition suggests concerns about job substitution or the reliability of AI in critical tasks. On the other hand, despite its importance, Objective O5 faces the greatest opposition. This could be because some actors perceive that AI solutions do not yet guarantee complete accuracy and could increase accounting risks if not properly regulated. Regarding O4, although many actors consider human participation in accounting relevant, opposition could come from sectors that view automation as an inevitable path and believe that limiting its expansion could stifle innovation. The polarization in these objectives suggests that there are strategic tensions that could require negotiations or adjustments in their formulation.

Figure 4. Histogram of actors' involvement in 2MAO objectives

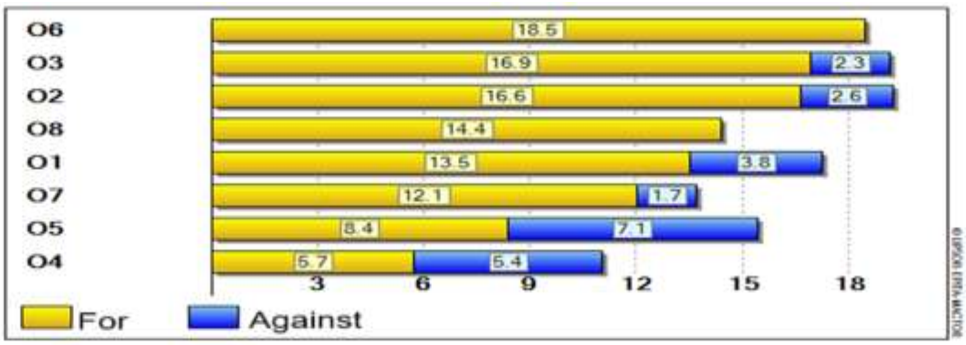


Source: Authors

The histogram in Figure 5 shows the level of mobilization of actors for or against each strategic objective. Compared with the level of commitment (2MAO), this graph allows for identifying which objectives are generating the most concrete action on the part of actors, either to promote or oppose them.

As seen in Figure 5, objectives O6, O3, and O2 are receiving the highest positive mobilization, indicating that actors not only agree with them but are actively promoting their implementation. Objectives O1 and O5 generate strong debate and mobilization against them, suggesting that there are active efforts to slow or condition the implementation of AI in accounting, especially in terms of regulation and reliability. Objective O4 has low mobilization, implying that the debate on the human role in accounting has not yet generated concrete actions, possibly due to a lack of consensus or because actors are waiting to see the impact of AI before acting.

Figure 5. Histogram of actors' involvement in 3MAO objectives



Source: Authors

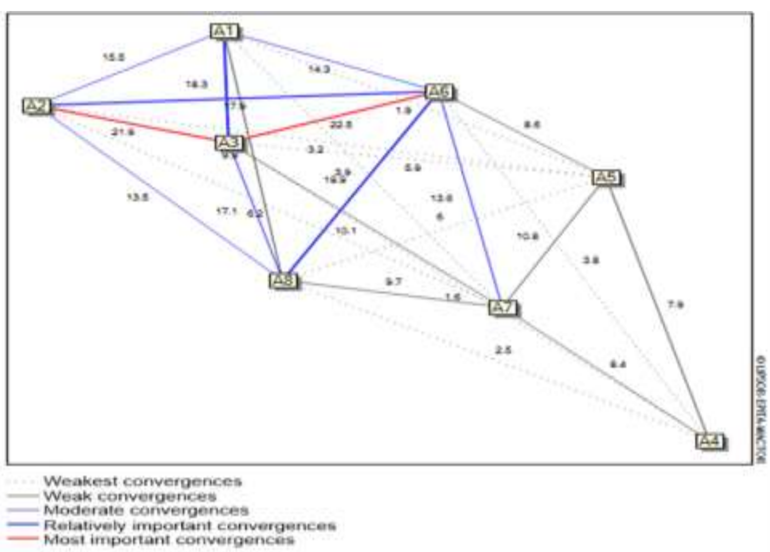
Convergences and divergences between actors

Figure 6 represents the convergences among the system's actors based on their strategies and objectives within the study. Convergence measures the degree of alignment among actors in terms of their interests and strategic positions with respect to the previously identified objectives. Relations between actors are classified using color coding and numerical values. Five levels of convergence are identified, from "weakest" to "most important," with the highest values indicating actors with strong overlap in strategic alignment and lower values indicating overlaps among the weakest actors.

In Figure 6, the relations between key actors are found between A3 and A6, which have a high level of convergence, suggesting they have a commonality in strategies and objectives. A2 and A3 also show a significant level of convergence, indicating strategies in key areas. In the case of A1 and A4, these relations show a low level of convergence, suggesting that their objectives and strategies are less aligned. A4 is the actor with the least overall convergence, which may reflect greater autonomy or divergence in strategies.

In this sense, actors with a higher level of convergence could group together in a strategic alliance to pursue the common goals of accounting digitalization or automation through ML, while weak relationships may reflect conflict or a lack of communication between key actors. This analysis facilitates the identification of potential coalitions or blockages in decision-making within the system.

Figure 6. Convergence graph



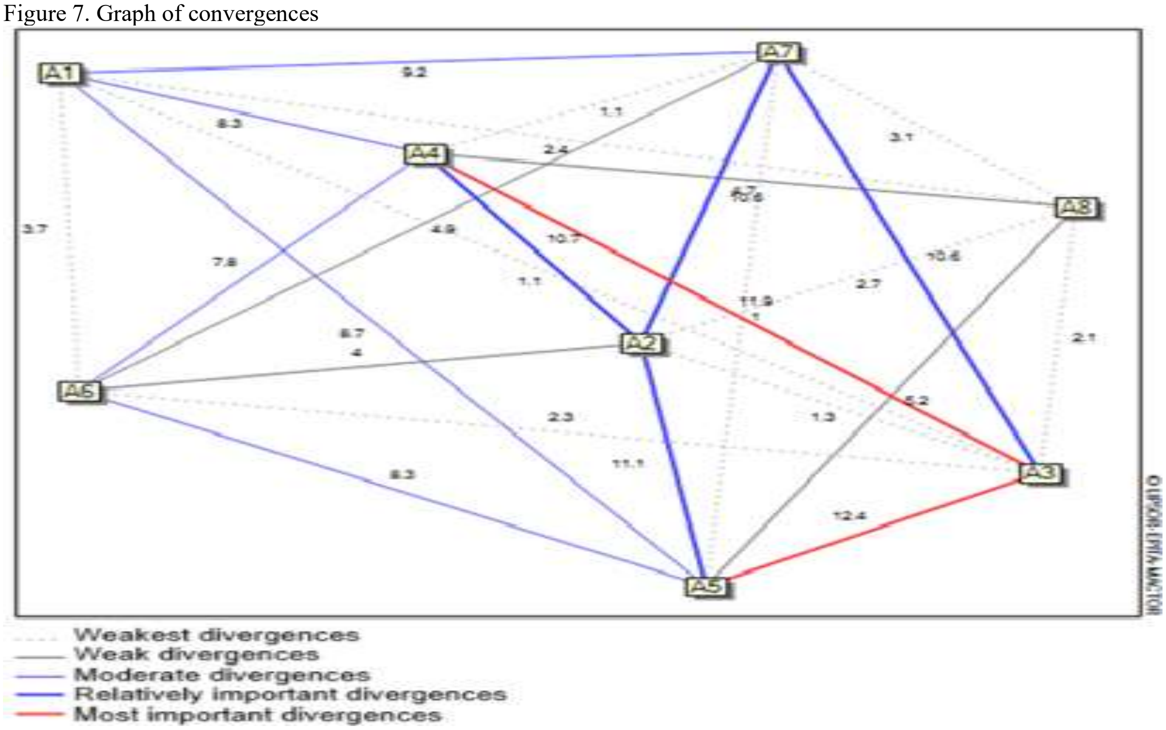
Source: Authors

Regarding the divergences presented, the illustrative graph in Figure 7 shows how the phenomenon occurs and the levels of divergence between actors in the context based on their strategies and objectives. Divergence represents significant differences in the actors' positions and strategic interests in relation to the objectives considered. The graph indicates five criteria for classifying relations between actors: from the level of "weakest divergences" to the level of "most important divergences." Thick lines indicate greater opposition between actors, and thinner lines indicate less significant divergences. Red lines indicate stronger divergences, while blue and gray lines indicate medium and weak divergences.

Actors A3 and A5, for their part, generate one of the most significant divergences (12.4) for this study, which allows for concluding that they have opposing strategies in relation to relevant topics. A3 and A4 also exhibit a significant divergence (11.9), which allows for inferring that they must be strategically divergent. A1 introduces less significant divergences with the other actors within the range of moderate divergences, but without a strong conflict with any of them. In contrast, A6 presents low divergences compared to other actors, which indicates that its position is more neutral or adaptive.

Actors with high levels of divergence could represent barriers to the implementation of ML strategies in accounting management, as their positions conflict. Significant differences may indicate the need for negotiations or strategic agreements to avoid decision-making deadlocks. A high level of divergence among key actors could generate resistance to technological changes or disagreements about the use of platforms such as ContaWeb-BI.

Figure 7. Graph of convergences



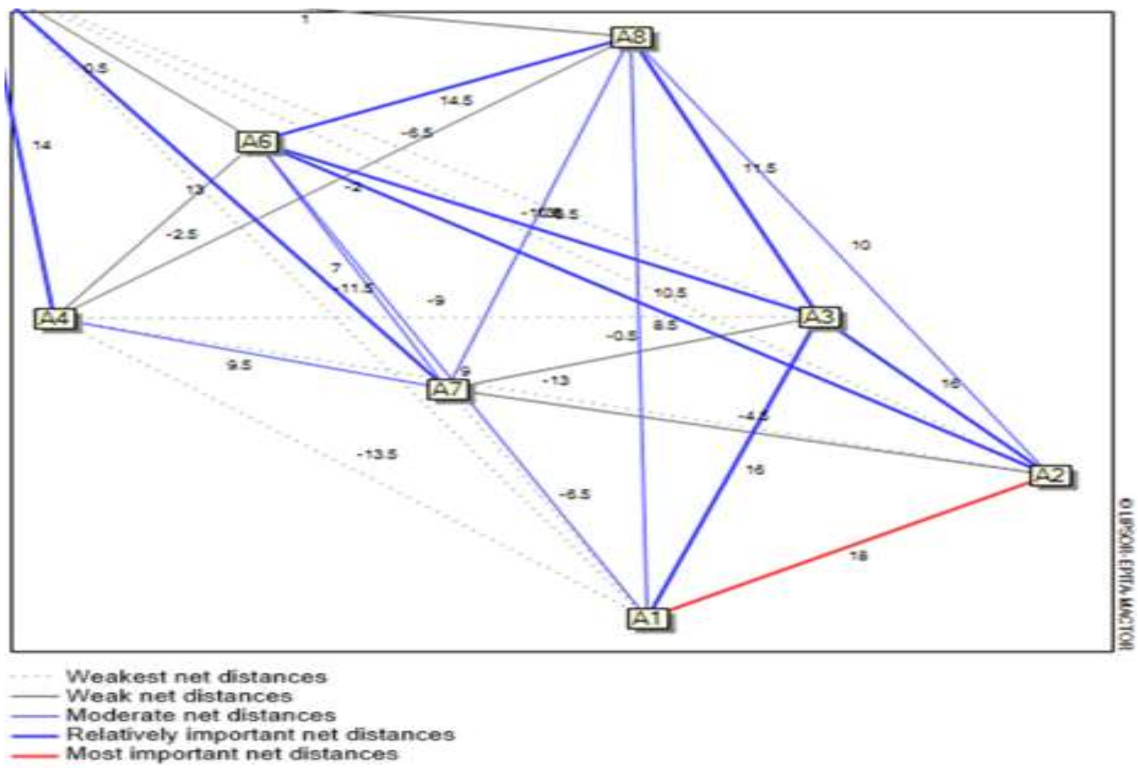
Source: Authors

Finally, the graph in Figure 8 represents the net distance between actors based on their strategic positions and influence relations. Net distance refers to the total difference between actors' positions, considering both convergences and divergences. A high net distance indicates a significant gap between two actors in terms of their strategies and interests, while a low net distance suggests that the actors have relatively similar or aligned positions. The lines are color-coded, with red lines representing the most significant distances, and blue and gray lines indicating smaller distances.

As seen in Figure 8, A1 and A2 have the highest net distance (18), indicating that these two actors have very different and possibly incompatible strategic stances in several aspects. A1 and A3 also show considerable distance (16), suggesting significant differences in their strategies or level of influence. A5 has weak net distances with several actors, indicating that its stance may be more neutral or intermediate within the system.

In this sense, actors with high net distances can represent obstacles to coordination and joint decision-making. Significant differences between key actors can generate conflicts or disagreements over the implementation of ML and accounting digitalization strategies. Identifying and reducing these distances is essential to facilitate collaboration and avoid blockages in the system's evolution.

Figure 8. Graph of net distances between actors



Source: Authors

The net distances graph allows for visualizing which actors have the greatest strategic differences and where conflicts or a lack of cooperation could arise. Reducing these net distances through negotiations and agreements could be key to aligning actors' interests around accounting digitalization and the use of ML.

Discussions

The results of the MACTOR analysis provided a detailed view of the convergence/divergence of the strategic objectives of the actors involved in the implementation of ML tools in accounting. This section compares the study's results with the corresponding scientific literature while discussing their implications for strategic decision-making regarding ML tools.

From the analysis of the MDI, it is concluded that there are some actors with the capacity to influence the direction and adoption of the accounting digitalization strategy based on ML, as well as other actors with the capacity for dependence. Specifically, actors classified as dominant have significant decision-making and guidance capacity, while dominated actors depend on the dominant actors. This result is similar to that shown in recent studies on governance in the digital transformation of financial companies, which show that accounting automation is driven by dominant actors with investment and technological development capacity (Yi et al., 2023).

The link actors, for their part, have both influence and dependence, which indicates that their position is strategic for the consolidation of accounting digitalization. The observed phenomenon is consistent with the information extracted from the research of Gomber et al. (2018), since digitalization in the financial services sector requires strong interaction between technology developers, regulators, and end users, which would contribute to achieving successful implementation.

On the other hand, the study of actors' involvement in strategic objectives (2MAO) showed a strong involvement in objectives related to operational efficiency and accounting automation (O1, O2, and O3), while there is some resistance to the objective referring to the preservation of the human role in accounting (O4). This result provides a sense of coherence with Grosu et al. (2023) because they highlight that there are still professionals who resist the automation of accounting processes. In the mobilization of actors (3MAO), it was found that the most powerful ones mobilize objectives related to transparency (O5) and financial security (O6), which is aligned with the state of the art corresponding to digital audits and the use of AI for the detection of accounting fraud (Kamuangu, 2024).

The convergence showed a strong alignment of interests for actors driving digitalization (A1, A3, A5), suggesting a clear orientation toward AI-driven accounting modernization. In contrast, the divergence graphs showed marked conflicts between actors trying to maximize efficiency (A2) and those trying to regulate or maintain employment (A4 and A6), which is also consistent with the literature showing a separation between automation and regulation in high-tech financial contexts (Obeng et al., 2024).

The net distance graph showed that strategically aligned actors, that is, those who dedicate efforts to building strong bridges between them, in turn tend to shorten the distance, allowing for the creation of strategic alliances and pacts to achieve common goals. However, significant barriers between actors with divergent positions are visible, which could justify the need for mediation strategies by reducing tensions. This is also in line with previous studies that highlight the importance of collaborative governance in the digital transformation of accounting (Grossi & Argento, 2022).

The results obtained with MACTOR suggest that the incorporation of ML tools in accounting is the result of a process comprised of actors pursuing different interests. The scientific literature emphatically highlights that digital transformation is associated with the interaction between those advancing the path of innovation and those regulating its implementation. Therefore, the adoption of a strategy that considers operational efficiency and regulation, as well as the adaptation of human capital, is suggested in order to achieve a balanced transition toward accounting automation.

Conclusions

The MACTOR analysis has revealed that there are dominant actors who favor accounting automation, while others are highly dependent on their decisions. The convergence of interests is greater among those in favor of digitalization, while there are contrasts with those who strive to regulate it and maintain human capital. The net distances between actors suggest that some groups have a strong tendency toward strategic alignment, thus facilitating potential alliances, while others have barriers that hinder cooperation.

The reported results have several implications. First, for organizations, the introduction of ML in accounting must be approached strategically by studying the power relations between key actors (dominant and link). Second, for regulatory entities, it is important to design policies that balance technological innovation with the protection of employment and financial security. Finally, for academic research, the study highlights the need to study the digitalization of accounting from a multidimensional perspective, that is, from the technological, economic, and social perspectives.

Although the advancement of machine learning in accounting is inevitable, its implementation must take into account the interaction between different strategic actors. Indeed, mechanisms for dialogue and interaction must be promoted that contribute to reducing discrepancies and potentially forging agreements that favor the sustainable and balanced implementation of this type of technology.

In conclusion, the digitalization of accounting promoted by the ML is not a unilateral process, but rather a consequence of a complex series of strategic dynamics among different actors. As this study demonstrates, aligned interests and conflict management are determining factors for its implementation. Based on these findings, it is recommended to develop strategies that combine automation with regulation, in addition to the inclusion of human talent to ensure the success of the accounting digitalization process, ultimately achieving digital accounting.

References

1. Bendahan, S., Camponovo, G., & Pigneur, Y. (2004). Multi-issue actor analysis: tools and models for assessing technology environments. Journal of decision systems, 13(2), 223-253.

2. Ben-Daoud, M., El Mahrad, B., Moroşanu, G., Elhassnaoui, I., Moumen, A., El Mezouary, L., & et, a. (2023). Stakeholders' interaction in water management system: insights from a MACTOR analysis in the R'Dom sub-basin, Morocco. Environmental Management, 71(6), 1129-1144.

3. Bertomeu, J., Cheynel, E., Floyd, E., & Pan, W. (2021). Using machine learning to detect misstatements. . Review of Accounting Studies, 26, 468-519.

4. Bhimani, A. (2020). Digital data and management accounting: why we need to rethink research methods. Journal of management control, 31(1), 9-23.

5. Cai, C., Linnenluecke, M., Marrone, M., & Singh, A. (2019). Machine learning and expert judgement: analyzing emerging topics in accounting and finance research in the Asia–Pacific. Abacus, 55(4), 709-733.

6. Chae, H. (2024). In search of gazelles: machine learning prediction for Korean high-growth firms. Small Business Economics, 62(1), 243-284.

7. Chakri, P., Pratap, S., & Gouda, S. (2023). An exploratory data analysis approach for analyzing financial accounting data using machine learning. Decision Analytics Journal, 7, 100212.

8. Chowdhury, E. (2023). Integration of artificial intelligence technology in management accounting information system: an empirical study. In Novel financial applications of machine learning and deep learning: algorithms, product modeling, and applications.Cham: Springer International Publishing, 35-46.

9. Ding, K., Lev, B., Peng, X., Sun, T., & Vasarhelyi, M. (2020). Machine learning improves accounting estimates: Evidence from insurance payments. Review of accounting studies, 25(3), 1098-1134.

10. Duan, H., Vasarhelyi, M., Codesso, M., & Alzamil, Z. (2023). Enhancing the government accounting information systems using social media information: An application of text mining and machine learning. International Journal of Accounting Information Systems, 48, 100600.

11. Elmsalmi, M., & Hachicha, W. (2014). Risk mitigation strategies according to the supply actors' objectives through MACTOR method. . IEEE In 2014 International Conference on Advanced Logistics and Transport (ICALT), 362-367.

12. Fieberg, C., Hesse, M., Loy, T., & Metko, D. (2022). Machine learning in accounting research. In Diginomics research perspectives: The role of digitalization in business and society. Cham: Springer International Publishing, 105-124.

13. Gomber, P., Kauffman, R., Parker, C., & Weber, B. (2018). On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. Journal of management information systems, 35(1), 220-265.

14. Grossi, G., & Argento, D. (2022). The fate of accounting for public governance development. Accounting, Auditing & Accountability Journal, 35(9), 272-303.

15. Grosu, V., Cosmulese, C., Socoliuc, M., Ciubotariu, M., & Mihaila, S. (2023). Testing accountants' perceptions of the digitization of the profession and profiling the future professional. Technological Forecasting and Social Change, 193, 122630.

16. Hasan, A. (2021). Artificial Intelligence (AI) in accounting & auditing: A Literature review. Open Journal of Business and Management, 10(1), 440-465.

17. Herrera, J. (2017). La investigación cualitativa. UDGVirtua. Retrieved from http://biblioteca.udgvirtual.udg.mx/jspui/handle/123456789/1167

18. Ionescu, L. (2022). Machine learning-based decision-making systems, cloud computing and blockchain technologies, and big data analytics algorithms in accounting and auditing. Economics, Management, and Financial Markets, 17(4), 9-26.

19. Kamuangu, P. (2024). A Review on Financial Fraud Detection using AI and Machine Learning. . Journal of Economics, Finance and Accounting Studies, 6(1), 67-77.

20. Lei, X., Mohamad, U., Sarlan, A., Shutaywi, M., Daradkeh, Y., & Mohammed, H. (2022). Development of an intelligent information system for financial analysis depend on supervised machine learning algorithms. . Information Processing & Management, 59(5), 103036.

21. Liaras, E., Nerantzidis, M., & Alexandridis, A. (2024). Machine learning in accounting and finance research: a literature review. Review of Quantitative Finance and Accounting, 63(4), 1431-1471.

22. Makmun, M., Fahmid, I., Ali, M., Saud, Y., & Rahmadanih, R. (2024). Power relations among actors in laying hen business in Indonesia: A MACTOR analysis. Open Agriculture, 9(1), 20220334.

23. Nielsen, S. (2022). Management accounting and the concepts of exploratory data analysis and unsupervised machine learning: a literature study and future directions. Journal of Accounting & Organizational Change, 18(5), 811-853.

24. Obeng, S., Iyelolu, T., Akinsulire, A., & Idemudia, C. (2024). The transformative impact of financial technology (FinTech) on regulatory compliance in the banking sector. World Journal of Advanced Research and Reviews, 23(1), 2008-2018.

25. Pozo-Antúnez, J., Molina-Sánchez, H., Ariza-Montes, A., & Fernández-Navarro, F. (2021). Promoting work Engagement in the Accounting Profession: a Machine Learning Approach. Social Indicators Research: An International and Interdisciplinary Journal for Quality-of-Life Measurement, 157(2), 653-670.

26. Quinteros, J., & Hamann, A. (2017). Planeamiento estratégico prospectivo. Bogotá: Ecoe Ediciones.

27. Ranta, M., Ylinen, M., & Järvenpää, M. (2023). Machine learning in management accounting research: Literature review and pathways for the future. European Accounting Review, 32(3), 607-636.

28. Riadh, H. (2022). Intelligent tourism system using prospective techniques and the Mactor methodology: a case study of Tunisian tourism. Current Issues in Tourism, 25(9), 1376-1398.

29. Tuzcuoğlu, T. (2023). Machine Learning Use Case Discovery and Implementation in the Finance and Accounting Domains of Companies. Florya Chronicles of Political Economy, 9(2), 89-106.

30. Van den Bogaerd, M., & Aerts, W. (2011). Applying machine learning in accounting research. . Expert Systems with Applications, 38(10), 13414-13424.

31. Yi, Z., Cao, X., Chen, Z., & Li, S. (2023). Artificial intelligence in accounting and finance: Challenges and opportunities. IEEE Access, 11, 129100-129123.