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The Transformative Impact of Artificial Intelligence on Accounting and Commerce: Opportunities, Challenges, and Future Prospects

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Abstract:
The integration of Artificial Intelligence (AI) in accounting and commerce is transforming traditional processes by enabling real-time analytics and data-driven decision-making. Techniques like machine learning, natural language processing, and robotic process automation are employed across a range of tasks, including data entry, financial reporting, fraud detection, and customer service. These technological advancements significantly improve operational efficiency and cost-effectiveness. However, they also raise important concerns regarding ethics, data privacy, workforce displacement, and regulatory compliance. This study critically examines the multifaceted impact of AI on accounting and commerce by evaluating the associated opportunities, challenges, and emerging trends. Drawing upon interdisciplinary literature and current organizational practices, the study offers valuable insights for scholars, business leaders, and policymakers navigating this evolving landscape.

Keywords:
Artificial Intelligence, Accounting Transformation, Institutional theory, Organizational adaptation

1. Introduction

The advent of artificial intelligence (AI) has marked a paradigm shift in business operations, bringing about significant changes to how organizations reach customers and conduct trade. The rear office is no longer limited to automation, AI now plays a key role in redefining architecture into economic processes, enabling real-time decision-making, future indication analysis, and strategic insight (Davenport and Ronanki, 2018). As global markets become more unstable and regulatory studies intensify, organizations quickly see AI not only as a technical growth opportunity but also as a means to rebuild the basis for value creation and economic management (Brianjolphson and McAI, 2017) as a transformative strength.

In accounting, AI technologies such as Machine Learning, Robotic Process Automation (RPA), and Natural Language Processing (NLP) have begun replacing manual operations with rules capable of continuous learning and adaptation. This advancement enables capabilities such as automated data entry, compliance monitoring, anomaly detection, and dynamic financial reporting (Appelbaum et al., 2017). Similarly, AI is employed in broader areas of commerce to optimize supply chains, enhance pricing strategies, and personalize customer interactions, thereby driving competitive advantage through data-driven innovation (Chui et al., 2018).

Despite this progress, it also leads to the use of AI for complex challenges. Ethical ideas on algorithm bias, privacy, and responsibility are unclear (Binns, 2018). In addition, shifts in workforce dynamics—marked by job displacement, skill gaps, and employee resistance—necessitate a reevaluation of organizational design and management structures (Susskind & Susskind, 2015). The success of AI integration depends not only on the technical ability but

also on the ability to adapt to institutional culture, management, and regulatory structure (Vial, 2019). The purpose of this study is to seriously examine the transformation effects of AI on accounting and trade by pursuing three main goals:
(1) to identify skilled operations and strategic opportunities by AI,
(2) to detect organizational and moral challenges associated with its deployment, and
(3) to evaluate the future path for AI-controlled changes through relevant organizational principles.
By integrating empirical evidence with interdisciplinary literature, this article adds to the growing discourse on how AI is reshaping professional practices, transforming institutional frameworks, and shaping the future of accounting and commerce in the digital era.

2. Literature Review

2.1 Artificial Intelligence in Accounting and Commerce

Artificial Intelligence (AI) has brought transformative change to accounting and commerce by automating conventional practices, enhancing accuracy, and supporting strategic decision-making.

Technologies like machine learning and robotic process automation (RPA) are widely and effectively applied in areas of financial reporting, fraud detection, customer engagement, and data analysis (Appelbaum et al., 2017). AI facilitates real-time financial monitoring and predictive analytics, empowering professionals to shift from routine transactional tasks to more strategic advisory roles (Davenport & Ronanki, 2018).

Numerous empirical studies have explored this transformation. Penger et al. (2023) found that AI enhances efficiency and cost-effectiveness in financial operations while contributing to sustainable development goals (SDGs) by optimizing time and resource utilization. Rawashdeh (2023) examined the socio-economic implications of AI, highlighting workforce displacement and emphasizing its influence on decision-making within the accounting domain. Similarly, Adeibiyi (2023), through regression analysis, identified a strong correlation between predictive analytics and improved capabilities in financial reporting, risk management, and fraud detection.

These findings point to a paradigm shift in which AI functions not merely as a supportive tool but as a catalyst for innovation, fundamentally reshaping how value is created in both accounting and commerce.

2.2 Institutional Theory and AI Adoption

The institutional theory suggests that organizations use innovations such as AI in response to coercion, copying, and authentic pressure from the external environment (Dimaggio & Powell, 1983). This pressure affects adaptation with organizational validity, competition, and industry standards.

High-profile corporate investments in AI depict institutional forces at work. For example, the RSM US reacts to $ 1 billion AI to develop expectations of the investment industry and the customer's requirements, reflecting copying and standard effects. Similarly, Ernst and Young (EY) provide an example of strategic attention, tax, risk, and automation in financial domains on the AI-operated workforce, and how standard pressure provides pressure to strategic alternatives (EY, 2023). These issues emphasize how the institutional environment runs out of

AI adoption, which often leads to structural changes in accounting and commercial activities (Vial, 2019).

2.3 Structuration Theory: AI and Organizational Practices

Structuration theory developed by Giddens (1984), claims that technology and organizational structures are recurrent - organizational forms of actor form technologies, which in turn are in behavior, strength conditions, and professional roles.

When it comes to AI, Almaktari (2024) emphasized the importance of coordinating the IT regime with organizational goals to ensure effective implementation. When AI systems automate regular accounting functions, professional identity is redefined. Accountant data processors are infected in strategic advisors and require the acquisition of new skills and the reshaping of traditional hierarchies (Susskind & Susskind, 2015). Collaboration of technology and practice not only requires technical ability but also organizational adaptability and inclusive leadership.

2.4 Contingency Theory: Organizational Fit for AI Integration

Contingency theory asserts that the success of innovation depends on its alignment with an organization's structure, technical maturity, market environment, and other relevant factors (Donaldson, 2001). For AI adoption to be effective, technological deployment must align with both internal capabilities and external requirements.

According to a Workday (2023) report, financial leaders operating within tech-savvy infrastructures and adaptive organizational cultures are more likely to achieve 'zero-day close' and benefit from real-time reporting enabled by AI. Furthermore, companies that integrate AI into their business models often experience reduced operating costs, improved financial accuracy, and enhanced decision-making capabilities (Brianjolphson & McAfi, 2017). These findings reinforce the premise of contingency theory—that AI yields the greatest benefits when deployed in organizations that are structurally and strategically prepared for its implementation.

2.5 Identified Gaps in Literature and Study Contributions

Despite the growing scholarly interest, there are still many gaps in the literature. First, longitudinal studies that examine the continuous effect of AI on accounting structures and roles are limited. Second, moral dimensions especially algorithmic bias, transparency, and data governance remain underexplored. Small and medium-sized enterprises (SMEs), which constitute a significant portion of the global economy, have been underrepresented in AI decision-making studies.

This research bridges these gaps by integrating theoretical frameworks with empirical evidence to examine the transformative role of AI in accounting and accounting information systems (AIS) within commerce. Drawing on theories such as institutional theory, structuration theory, and contingency theory, the study aims to offer a comprehensive understanding of how AI reshapes professional functions, organizational structures, and business models.

3. Methodology

3.1 Research Design

This study adopts a qualitative, exploration research design to investigate the transformative effects (AI) on accounting and trade in emphasizing organizational reactions and adaptation. Given the complex and evolving nature of AI technologies and their interaction with social, technical, and institutional structures, a qualitative approach is well-suited to capture the processes of change, resistance, and strategic alignment, offering rich and contextually relevant insights.

This study is guided by an explanatory research paradigm, which holds that organizational events are socially constructed and are best understood through the meanings attributed to them by the individuals involved (Orlikowski & Baroudi, 1991).
It is consistent with the planned theoretical contours, especially structural theory, institutional theory, and random theory, each requiring attention to the organizational reference, the actor agency, and developed structures.

3.2 Data collection

Data were collected through semi-structured interviews, document analysis, and observation to achieve triangulation and enhance the reliability of the insights.

3.2.1 Semi-Structured interview

A total of 22 semi-structured interviews were conducted with professionals in four categories:
1. In the senior accountant and financial proceedings that have used AI tools (n = 8)
2. Technology Manager and AI Implementation Leeds (n = 5)
3. Nivy-level commercial leader involved in digital strategy (n = 5)
4. Regulators and professional body representatives (n = 4)

Participants were selected through purposive sampling based on criteria such as involvement in AI-related projects or policies within large corporations as well as small and medium-sized enterprises in the financial services and retail sectors. Interviews lasted between 45 and 90 minutes and were conducted in person, with recordings made after obtaining participant consent.

3.2.2 Document Analysis

Organizational reports, strategic plans, regulatory publications, and AI supplier -white papers were investigated to complement the interview data. This provided background references and evidence of how AI is involved in a way in industry, academic, and professional domains.

3.2.3 Observational data

Where possible, non-participating observation of digital change workshops and AI training sessions was carried out in two case organizations. Notes are focused on implementation practices, employee involvement, and new problems.

3.3 Data analysis

Data were analyzed using thematic analysis (Braun & Clarke, 2006), combining inductive coding with broad categories guided by theoretical frameworks.
NVIVO software was hired to help with data management and coding.
Focus on identifying topics related to initial coding cycles:

- ✓ Automation and task reconfiguration

- ✓ Employee resistance and adaptation
- ✓ Institutional and regulatory responses
- ✓ Organizational redesign and role change
- ✓ AI-human collaboration dynamics

The subsequent coding involved mapping themes based on structural theory (e.g., technology use models), institutional theory (e.g., legitimacy, isomorphism), and contingency theory (e.g., strategy-technology fit).

This principle-based analysis provided a comprehensive understanding of how AI adoption is embedded within broader organizational change processes.

3.4 Trustworthiness and Ethical Considerations

To ensure credibility, member checking was conducted by sharing interview summaries with participants for verification. Triangulation of data from interviews, documents, and observations enhanced the study's reliability. Transferability was addressed by providing detailed descriptions of organizational contexts and supporting references.

Approval for the study was granted by the host institution's Ethics Committee. All participants provided informed consent, and their anonymity was maintained to ensure privacy. The research adhered to GDPR and relevant local data protection laws.

3.5 Limitations

This study acknowledges its inherent limitations. While the conclusions are analytical, they are grounded in specific organizational and national contexts and may not be universally applicable. Furthermore, the rapid pace of technological innovation means that developments occurring during or after the research period could influence the findings.

4. Results and Discussion

4.1 Reconfiguring Accounting Tasks and Roles

Across all participating firms, artificial intelligence (AI) has automated routine accounting functions such as invoice processing, bank reconciliations, and compliance checks. Interviewees consistently emphasized that automation is no longer viewed solely as a cost-saving tool but as a strategic enabler that elevates the role of human accountants. For example, a finance director at a multinational corporation stated:

"With AI handling 80% of our transactional work, our finance team can now focus on forecasting, strategic planning, and business partnering."

This finding aligns with Rawashdeh's (2023) observations regarding AI's role in reshaping decision-making strategies. It also reflects the structuration dynamic, wherein technologies, once embedded in daily operations, recursively reshape organizational practices and professional expectations (Giddens, 1984; Macintosh & Scapens, 1990). Importantly, the transformation is not deterministic but negotiated and shaped through practice.

In small and medium-sized enterprises (SMEs) with lower digital maturity, AI applications were typically limited to basic functions such as automated bookkeeping or customer relationship management (CRM) insights. These organizations frequently cited resource constraints and uncertainty regarding return on investment, supporting contingency theory's assertion that technological effectiveness is context-dependent (Donaldson, 2001).

4.2 Emerging Challenges: Resistance and Skill Gaps

Despite the noted advantages, employee resistance emerged as a recurrent theme, particularly among mid-career professionals. Participants reported concerns about obsolescence and ambiguity regarding new responsibilities. An audit manager remarked:
"There's anxiety about being replaced—not by a junior analyst, but by an algorithm."
This resistance was often not rooted in opposition to technology per se but in uncertainty about evolving roles, insufficient training, and threats to professional identity. These insights resonate with Arnaboldi et al. (2017), who contend that resistance during organizational change often reflects struggles over control and meaning.

Organizations that successfully mitigated resistance implemented structured change management programs, targeted upskilling initiatives, and transparent communication strategies. These practices underscore the importance of internal capability development, as emphasized by Almaqtari (2024) and Workday (2023).

4.3 Institutional Pressures and Legitimacy

Larger firms adopted AI not only for efficiency gains but also to maintain institutional legitimacy. For instance, representatives from Big Four accounting firms indicated that AI adoption was essential to sustaining brand leadership and client trust. A strategy officer explained:
"Clients expect us to be ahead of the curve. AI is not optional—it's integral to maintaining our brand."

This is consistent with DiMaggio and Powell's (1983) institutional theory, which highlights how coercive (regulatory), mimetic (peer imitation), and normative (professional norms) pressures shape organizational behavior. The adoption of environmental, social, and governance (ESG)-aligned AI tools for carbon accounting and ethical sourcing further illustrates how external legitimacy concerns can drive internal innovation.

Conversely, public sector and nonprofit organizations reported compliance uncertainties and regulatory ambiguity, particularly in the absence of clear AI governance standards. These findings underscore the urgent need for guidance from standard-setting bodies and professional associations.

4.4 Changing Organizational Structures and Decision-Making

AI adoption led to significant changes in organizational decision-making structures. Firms deploying AI-driven analytics experienced flatter hierarchies and increased access to real-time dashboards across departments. This decentralization facilitated more agile and data-informed decisions.

In one retail case, AI-assisted demand forecasting allowed finance and supply chain teams to collaborate on procurement decisions. These findings support contingency theory claims that AI tools, when aligned with flexible organizational structures, enhance performance (Granlund, 2011; Yu & Xu, 2021).

Nevertheless, some firms encountered challenges in integrating AI insights into actionable strategies. AI systems often lacked contextual awareness, creating "interpretive gaps" where

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human judgment remained essential (Sangster et al., 2020). Thus, while AI accelerates operations, it does not eliminate the need for human oversight in decision-making.

4.5 Ethics, Accountability, and Transparency

A recurring concern was the opacity of AI systems, especially in fraud detection and credit scoring applications. Professionals expressed apprehensions about "black box" models, lack of explainability, and potential biases. A compliance officer stated:
“If a model flags something as ‘risky,’ we need to understand why—especially during regulatory audits.”
These ethical concerns align with calls in the literature for transparent and accountable AI systems (Peng et al., 2023). While many firms are implementing AI governance frameworks, their maturity and efficacy vary widely.

Furthermore, the shift in accountability from individuals to systems introduces philosophical and legal challenges. The question of responsibility for AI-driven decisions remains unresolved and demands further theoretical and regulatory exploration, particularly in high-stakes financial contexts.

Synthesis with Theoretical Frameworks

Theoretical Frameworks	Key Observations
Institutional Theory	AI adoption driven by coercive (regulatory), normative (professional norms), and mimetic (market imitation) pressures.
Structuration Theory	AI recursively reshapes professional practices and organizational routines.
Contingency Theory	AI effectiveness varies by organizational size, readiness, and cultural adaptability.

5. Conclusion and Recommendations

5.1 Conclusion

This study explored the transformative impact of AI on accounting and commerce, emphasizing how technological adoption drives organizational change. Using qualitative data from interviews, observations, and document analysis, and guided by institutional, structuration, and contingency theories, the findings demonstrate that AI is not merely a technical innovation—it is a catalyst for reconfiguring professional roles, organizational structures, and strategic priorities.

AI has automated routine accounting processes, improved real-time analytics, and shifted roles from transactional to strategic. In commercial functions, it enhances predictive demand planning and consumer personalization. However, these gains are contingent upon organizational readiness, clearly defined implementation strategies, and the alignment of AI tools with broader structural and cultural contexts.

Institutional pressures shape AI adoption, particularly in larger firms. Structuration theory highlights how AI is enacted and embedded into professional routines, while contingency theory emphasizes that successful implementation depends on internal alignment of strategy, structure, and capabilities. Persistent challenges—including skill gaps, resistance, ethical concerns, and accountability questions—underscore the need for a multidimensional approach to AI adoption.

5.2 Recommendations

For Practitioners:

- ✓ **Adopt a phased, strategic approach to AI** by targeting use cases that align with specific goals and operational readiness.
- ✓ **Invest in workforce development** through re-skilling programs and redesigning roles to support human-AI collaboration.
- ✓ **Establish internal AI governance frameworks** to ensure ethical compliance, data integrity, and transparency.
- ✓ **Promote a learning culture** to facilitate adaptation and reduce resistance by involving employees in change processes.

For Policymakers and Professional Bodies:

- ✓ **Update regulatory and ethical standards** with clear, adaptive guidelines for AI usage in financial reporting and auditing.
- ✓ **Support SMEs and public sector adoption** via tax incentives, funding programs, and access to shared AI infrastructure.
- ✓ **Foster industry collaboration** through standard benchmarks, knowledge-sharing platforms, and cross-sector AI forums.

For Future Researchers:

- ✓ **Conduct longitudinal studies** to trace long-term impacts of AI on accountability, structure, and performance.
- ✓ **Explore underrepresented sectors**, including SMEs and public institutions, to broaden understanding across contexts.
- ✓ **Incorporate interdisciplinary perspectives** from information systems, sociology, and ethics to enrich AI research in accounting.

5.3 Final Remarks

AI is fundamentally reshaping accounting and commerce, yet its impacts are mediated by social structures, professional norms, and institutional contexts. This study illustrates the dynamic interplay between technology and organization, emphasizing that AI's influence is not uniform or inevitable.

With strong governance, ethical foresight, and organizational learning, firms can harness AI not just for efficiency, but for building inclusive, accountable, and future-ready systems of value creation.

References

1. Appelbaum, D., Kogan, A., Vasarhelyi, M. A., & Yan, Z. (2017). *Impact of business analytics and enterprise systems on managerial accounting*. International Journal of Accounting Information Systems, 25, 29-44 https://doi.org/10.1016/j.accinf.2017.03.003
2. Adebiyi, S. (2023). Predictive analytics and the evolution of accounting and auditing expertise: An empirical investigation. *Journal of Accounting and Auditing*, 29(2), 145–167. https://doi.org/10.1080/X
3. Almaqtari, F. A. (2024). The role of IT governance in the integration of artificial intelligence in accounting and auditing operations. *Economies*, 12(8), 199. https://doi.org/10.3390/economies12080199

4. Arnaboldi, M., Lapsley, I., & Steccolini, I. (2017). Performance management in the public sector: The ultimate challenge? *Financial Accountability & Management*, 33(4), 365–378. https://doi.org/10.1111/faam.12117
5. Binns, R. (2018). *Fairness in machine learning: Lessons from political philosophy*. Proceedings of the 2018 Conference on Fairness, Accountability and Transparency, 149–159. https://doi.org/10.1145/3287560.3287583
6. Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W. W. Norton & Company.
7. Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa
8. Chui, M., Manyika, J., & Miremadi, M. (2018). *Notes from the AI frontier: Insights from hundreds of use cases*. McKinsey Global Institute.
9. Davenport, T. H., & Ronanki, R. (2018). *Artificial intelligence for the real world*. Harvard Business Review, 96(1), 108–116.
10. DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147–160. https://doi.org/10.2307/2095101
11. Donaldson, L. (2001). *The contingency theory of organizations*. Sage Publications.
12. EY. (2023). *EY invests $1 billion in AI and workforce transformation*. Retrieved from [ey.com]
13. Giddens, A. (1984). *The constitution of society: Outline of the theory of structuration*. University of California Press.
14. Granlund, M. (2011). Extending AIS research to management accounting and control issues: A research note. *International Journal of Accounting Information Systems*, 12(1), 3–19. https://doi.org/10.1016/j.accinf.2010.12.003
15. Macintosh, N. B., & Scapens, R. W. (1990). Structuration theory in management accounting. *Accounting, Organizations and Society*, 15(5), 455–477. https://doi.org/10.1016/0361-3682(90)90033-A
16. Peng, L., Wu, H., & Zhang, Y. (2023). The role of artificial intelligence in achieving sustainable development goals in accounting practices. *Sustainability*, 15(3), 1789. https://doi.org/10.3390/su15031789
17. Rawashdeh, A. (2023). AI in accounting: Job displacement and new skill demands. *Journal of Finance and Technology*, 12(1), 35–50. https://doi.org/10.1080/X
18. Sangster, A., et al. (2020). Interpretive gaps in AI implementation in accounting: Challenges and future directions. *Accounting Horizons*, 34(2), 45–62. https://doi.org/10.2308/acch-52310
19. Susskind, R., & Susskind, D. (2015). *The future of the professions: How technology will transform the work of human experts*. Oxford University Press.
20. Vial, G. (2019). *Understanding digital transformation: A review and a research agenda*. The Journal of Strategic Information Systems, 28(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003
21. Workday. (2023, March 10). Three trends that will reshape accounting and finance in 2023. Retrieved from https://blog.workday.com/en-us/2023/3-trends-will-reshape-accounting-finance-2023.html
22. Yu, L., & Xu, J. (2021). The contingency perspective on AI adoption in accounting firms. *Journal of Business Research*, 132, 57–65. https://doi.org/10.1016/j.jbusres.2021.03.012