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An Intelligent Framework for Prioritizing Financial Accounting Strategies in Electronic Banking Based on Computational Intelligence

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ABSTRACT

The purpose of this study is to develop an intelligent and transparent framework for prioritizing financial accounting strategies within the context of electronic banking, in a manner that simultaneously leverages high computational capacity while addressing the essential requirements of transparency, auditability, and regulatory compliance in financial accounting systems. In terms of purpose, the research is applied–developmental, and in terms of methodology, it adopts a mixed-methods approach (qualitative–quantitative). The study was conducted in three phases. In the qualitative phase, novel financial accounting indicators relevant to electronic banking were identified and screened using content analysis and the fuzzy Delphi technique. In the quantitative phase, the interrelationships among criteria were modeled and weighted using the Analytic Network Process (ANP), in order to account for nonlinear dependencies between accounting and technical criteria. In the decision-making phase, strategic alternatives were prioritized through the application of the TOPSIS and SAW methods, and the algorithms were implemented in the Python environment to enhance computational transparency and reproducibility. The findings indicate that criteria such as reporting transparency, data governance, cybersecurity, and real-time auditability carry the greatest weight in the selection of financial accounting strategies. The results of the TOPSIS model show that strategies such as continuous auditing and blockchain-based accounting systems, despite their higher cost and complexity, achieve the highest priority due to their superiority in transparency and trustworthiness. The convergence of results obtained from the TOPSIS and SAW methods confirms the robustness and validity of the proposed model. Overall, the study demonstrates that financial accounting in electronic banking has evolved from a mere event-recording system into an intelligent data governance ecosystem. By integrating computational intelligence with accounting principles, the proposed framework substantially bridges the gap between accounting theory and the practical requirements of digital banking. The results of this research can serve as a reliable foundation for financial managers, auditors, and banking policymakers in the design and selection of modern accounting strategies.

Keywords: Financial accounting; computational intelligence; electronic banking; multi-criteria decision-making; analytic network process; TOPSIS

Introduction

The rapid diffusion of artificial intelligence (AI) across financial and accounting domains has fundamentally reshaped the architecture, objectives, and operational logic of contemporary accounting systems. Accounting,

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which was traditionally centered on historical data recording, periodic reporting, and compliance-oriented procedures, is increasingly evolving toward a dynamic, data-driven, and intelligence-enabled function capable of supporting real-time decision-making, risk management, and strategic governance. This transformation has been accelerated by the growing complexity of financial transactions, the expansion of digital banking and FinTech ecosystems, and heightened regulatory expectations regarding transparency, accuracy, and accountability in financial reporting (1, 2). In this context, AI is no longer perceived merely as a supportive technology but rather as a structural force that redefines the epistemological foundations and functional boundaries of financial accounting.

Recent studies emphasize that AI-driven accounting systems significantly enhance the quality, timeliness, and reliability of financial information by automating data processing, minimizing human error, and enabling advanced analytical capabilities (3, 4). The integration of machine learning algorithms, rule engines, deep learning models, and natural language processing tools has enabled accounting systems to move beyond deterministic rule-based processing toward adaptive, predictive, and self-learning architectures. These capabilities are particularly critical in environments characterized by high transaction volumes, complex regulatory frameworks, and increasing exposure to financial risk and fraud (5, 6). Consequently, AI has emerged as a central pillar in the modernization of accounting and financial management infrastructures.

A substantial body of literature documents the role of AI in improving financial reporting quality, reducing accounting errors, and strengthening internal control systems. Empirical evidence suggests that AI-enabled accounting systems improve data consistency, reduce processing delays, and enhance the accuracy of financial statements, thereby increasing stakeholder confidence in reported financial information (7, 8). Moreover, AI applications in auditing—such as continuous auditing, anomaly detection, and automated risk assessment—have demonstrated considerable potential in improving audit quality and reinforcing the credibility of financial reporting processes (9, 10). These developments indicate a paradigmatic shift from ex post verification toward proactive and preventive financial oversight.

Beyond reporting and auditing, AI has also been widely applied in taxation, compliance, and regulatory monitoring. Studies conducted in both developed and emerging economies show that AI-driven systems enhance tax compliance by improving detection of evasion patterns, automating regulatory enforcement, and increasing the efficiency of tax administration processes (11, 12). The growing alignment between AI technologies and regulatory frameworks has given rise to RegTech solutions that enable real-time compliance monitoring and adaptive regulatory responses. This alignment is particularly relevant in digital banking environments, where traditional compliance mechanisms struggle to keep pace with the speed and complexity of financial innovations (13, 14).

Despite these advancements, the literature also highlights significant challenges associated with the adoption of AI in accounting and financial management. These challenges include algorithmic opacity, data governance risks, ethical concerns, cybersecurity vulnerabilities, and the potential erosion of professional judgment. Several scholars argue that while AI improves technical efficiency, it may also introduce new forms of systemic risk if not embedded within robust governance frameworks (15, 16). In particular, the “black box” nature of some AI models raises concerns regarding explainability, auditability, and accountability, which are core principles of financial reporting and assurance. Addressing these concerns requires not only technological solutions but also the development of conceptual and methodological frameworks that align AI capabilities with accounting standards and governance norms.

Another critical dimension discussed in the literature is the transformation of accounting roles and competencies in the age of AI. As routine accounting tasks become increasingly automated, the professional focus of accountants is shifting toward interpretation, judgment, and strategic analysis. This transition necessitates new skill sets that combine accounting expertise with data analytics, information systems, and AI literacy (17, 18). At the organizational level, the integration of AI into accounting systems also reshapes decision-making structures by enabling real-time performance monitoring, scenario analysis, and predictive forecasting (19). These changes reinforce the view that AI is not merely a technological upgrade but a catalyst for organizational and institutional transformation in financial management.

Within this evolving landscape, the shift from financial accounting toward management-oriented and intelligence-driven accounting models has received growing scholarly attention. Research indicates that AI facilitates the integration of financial accounting and management accounting by enabling continuous data flows, automated rule enforcement, and real-time performance evaluation (20, 21). This integration supports strategic decision-making by linking financial data with operational, environmental, and sustainability metrics. In particular, the use of AI in sustainability and digital reporting has been shown to improve the quality and credibility of non-financial disclosures, thereby responding to increasing stakeholder demands for integrated and transparent reporting (22).

Nevertheless, while existing studies provide valuable insights into specific applications of AI in accounting—such as auditing, taxation, forecasting, or reporting—they often remain fragmented and technology-centric. There is a notable lack of comprehensive decision-oriented frameworks that assist financial managers in prioritizing AI-based accounting strategies under conditions of uncertainty, competing objectives, and regulatory constraints. Many organizations face practical challenges in selecting among alternative AI-enabled accounting solutions, particularly when trade-offs exist between cost, transparency, compliance, feasibility, and strategic value (23, 24). This gap underscores the need for integrative models that combine accounting theory, computational intelligence, and multi-criteria decision-making approaches.

Multi-criteria decision-making (MCDM) methods offer a promising methodological foundation for addressing this gap. By systematically incorporating qualitative judgments and quantitative metrics, MCDM techniques enable decision-makers to evaluate complex alternatives across multiple, often conflicting criteria. Prior studies suggest that combining AI-driven analytics with MCDM frameworks enhances decision rationality, transparency, and robustness in financial management contexts (1, 2). However, empirical applications of such integrated frameworks in the domain of intelligent accounting strategy selection remain limited, particularly in the context of digital banking and advanced financial information systems.

Furthermore, the strategic implications of adopting AI-based accounting systems extend beyond technical efficiency to issues of trust, legitimacy, and governance. User trust in AI-enabled accounting systems has been identified as a critical mediating factor influencing the perceived quality and acceptance of financial reports (7). Similarly, the interaction between AI-based security mechanisms and customer or stakeholder confidence plays a vital role in the success of digital financial services (13). These findings highlight the necessity of evaluating accounting strategies not only from a technical or economic perspective but also from a governance and stakeholder-oriented viewpoint.

In light of these considerations, there is a growing consensus in the literature that future accounting systems must be designed as intelligent, transparent, and governance-oriented ecosystems rather than isolated technological tools. Such systems should integrate AI capabilities with robust data governance structures, regulatory compliance mechanisms, and decision-support functionalities. Developing practical frameworks that operationalize this integration and guide strategic prioritization remains a pressing research agenda (8, 23). Addressing this agenda requires interdisciplinary approaches that draw on accounting, information systems, computational intelligence, and decision sciences.

Accordingly, the present study seeks to respond to this research gap by developing an intelligent, decision-oriented framework for prioritizing AI-based financial accounting strategies in digital and banking environments, grounded in computational intelligence and multi-criteria decision-making methodologies, with the aim of supporting financial managers in selecting accounting strategies that maximize transparency, compliance, and strategic value.

Methods and Materials

From the perspective of research objectives, this study falls within the category of applied–developmental research, and in terms of its nature and implementation method, it adopts a mixed-methods approach with an emphasis on mathematical modeling. The underlying logic of the research methodology is to move away from the qualitative and subjective judgments of auditors and financial managers toward a precise and quantitative computational framework. The overall architecture of the study is designed in three consecutive phases, which are described in detail below.

In the first step, content analysis followed by the fuzzy Delphi technique is employed to identify the critical components of "financial accounting within the context of data governance." Given that variables such as the "fair value of algorithms" or the "level of regulatory adaptability (RegTech)" are inherently ambiguous, reliance on the literature alone is insufficient. Accordingly, open-ended questionnaires are administered to a panel of experts comprising senior auditors of banking systems, big data specialists, and risk managers. The output of this phase consists of the refinement of indicators and their classification into clusters and network nodes, which form the primary inputs of the decision-making model.

The core of the research methodology is the implementation of the Analytic Network Process (ANP). Unlike linear methods, this approach assumes the existence of bidirectional and feedback relationships between accounting criteria (such as reporting transparency) and technical criteria (such as cybersecurity and data quality). At this stage, pairwise comparison questionnaires are completed by experts. Subsequently, the initial supermatrix is constructed and normalized into a weighted supermatrix, and finally raised to limiting powers until convergence is achieved. Through this process, the final weights and relative importance of each data governance criterion in the quality of financial reporting are derived. These mathematical computations transform the uncertainty inherent in expert judgments into precise quantitative data.

After determining the exact weights of the criteria, the evaluation of alternatives is conducted. In this section, two complementary techniques are applied.

First, the TOPSIS method is used. By constructing the decision matrix, alternatives are ranked based on their Euclidean distance from the "positive ideal solution" (the best condition in terms of transparency and efficiency) and the "negative ideal solution" (the worst condition in terms of risk and cost). This method enables managers to identify which alternative is most similar to the optimal state of digital accounting.

Second, the SAW (Simple Additive Weighting) method is employed as a control tool to validate the results obtained from TOPSIS, ensuring that the rankings are not distorted by mathematical complexity.

The statistical population of both the qualitative and quantitative sections consists of banking industry experts and academics with expertise in the fields of management accounting and information technology. To assess the validity of the model, the inconsistency ratio in the ANP pairwise comparison matrices is used; if this ratio is less than 0.1, the consistency of judgments and the validity of the model are confirmed. In addition, a sensitivity analysis is conducted on the weights to determine the extent to which changes in data governance priorities affect the selection of the final accounting system. This stage functions as a "stress test" for the computational intelligence of the model.

Findings and Results

The findings of this study, which are derived from the rigorous implementation of computational intelligence algorithms and expert financial judgments, can be presented at three distinct yet interconnected levels. These results demonstrate how the accounting paradigm has shifted from the traditional "event-recording" approach to a modern "data-driven analytical" approach.

Table 1. Research Findings

Level of Analysis	Phase / Method	Key Component or Criterion	Description of Findings	Strategic Interpretation
First Level	Fuzzy Delphi	Data governance quality	Traditional accounting criteria such as historical cost and EPS are insufficient on their own	Transition from traditional financial statements to a data-driven ecosystem
First Level	Fuzzy Delphi	Algorithmic adaptability	Ability to automatically enforce AML rules and financial regulations	Accounting has become part of an intelligent supervisory system
First Level	Fuzzy Delphi	Security and trust	Data encryption and resistance to manipulation of financial information	Cybersecurity is an inherent component of digital financial reporting
First Level	Fuzzy Delphi	Valuation of intangible assets	Real-time valuation of data and artificial intelligence algorithms	Informational assets have become pillars of financial valuation
Second Level	ANP	Transparency and real-time auditing	Highest normalized weight among the criteria	Primary driver in the selection of intelligent accounting systems
Second Level	ANP	Cybersecurity ↔ reliability	Nonlinear dependency and high direct effect	Weakening security directly reduces reporting credibility
Second Level	ANP	Implementation cost	Lower weight compared to data governance	Cost is not the main barrier; transparency is the key factor
Third Level	TOPSIS	Blockchain-based accounting	Shortest distance from the positive ideal solution	First-ranked proposed system
Third Level	TOPSIS	Cloud accounting	Favorable but not optimal performance	Second rank
Third Level	TOPSIS	Traditional ERP systems	Greatest distance from the positive ideal solution	Lowest rank due to weak continuous auditing capabilities
Third Level	SAW	Validation of results	Full alignment with TOPSIS	Robustness and validity of computational results
Integrated	Final analysis	Opportunity cost of data governance	Cost of lack of transparency exceeds the cost of technology deployment	Strategic justification for investment in intelligent accounting

In this study, in order to move beyond purely theoretical models and to provide a practical tool for financial managers, the TOPSIS decision-making algorithm (Technique for Order Preference by Similarity to Ideal Solution) was implemented using the Python programming language and the powerful NumPy library. This computational code functions as the inferential engine of the proposed framework and is capable of automatically producing the final ranking of strategies by receiving the decision matrix and the weights derived from previous sections (such as entropy or DEMATEL).

The developed code processes the data through the following steps:

1. **Construction of the decision matrix:** The initial inputs consist of the scores of strategies with respect to criteria such as “cost reduction,” “transparency,” “regulatory compliance,” and “feasibility.”
2. **Vector normalization:** Applied to eliminate the effects of different measurement units.
3. **Determination of reference points:** Identification of the positive ideal solution (A^+) and the negative ideal solution (A^-) based on the type of criterion (benefit or cost).
4. **Calculation of Euclidean distances:** Measurement of the geometric distance of each alternative from the ideal points.
5. **Calculation of the final score (CL_i):** Determination of the relative closeness coefficient, which constitutes the basis for the final ranking.

The script developed to solve the model is presented below:

```
import numpy as np

# --------------------------------------------------------
# INPUT DATA SECTION
# --------------------------------------------------------
# Sample Data: Decision Matrix (Strategies x Criteria)
# Rows (Strategies):
#   S1: Continuous Auditing
#   S2: TDABC
#   S3: Smart ALM
#   S4: XBRL
#   S5: Fraud Detection
# Cols (Criteria):
#   [C1: Cost Efficiency, C2: Transparency, C3: Compliance, C4: Feasibility]
# Scale: 1-9 (Higher is better for benefit criteria)

data = np.array([
    [9, 8, 7, 6],  # S1
    [5, 6, 5, 5],  # S2
    [7, 5, 8, 6],  # S3
    [4, 9, 6, 7],  # S4
    [8, 7, 9, 5]   # S5
])

# Weights derived from Entropy Method or Expert Input
weights = np.array([0.3, 0.2, 0.3, 0.2])

# Criteria types: 1 for Benefit (max), -1 for Cost (min)
# Assuming all are Benefit criteria for this specific scenario
criteria_type = np.array([1, 1, 1, 1])
```

```
# --------------------------------------------------------
# ALGORITHM IMPLEMENTATION
# --------------------------------------------------------
def topsis_method(matrix, weights, types):
    # 1. Normalize the matrix (Vector Normalization)
    # Norm_X = X / sqrt(sum(X^2))
    norm_matrix = matrix / np.sqrt((matrix**2).sum(axis=0))

    # 2. Weighted Normalized matrix
    # V = Norm_X * W
    weighted_matrix = norm_matrix * weights

    # 3. Determine Ideal Best (A+) and Ideal Worst (A-)
    ideal_best = []
    ideal_worst = []

    for i in range(len(types)):
        if types[i] == 1: # Benefit Criterion
            ideal_best.append(weighted_matrix[:, i].max())
            ideal_worst.append(weighted_matrix[:, i].min())
        else: # Cost Criterion
            ideal_best.append(weighted_matrix[:, i].min())
            ideal_worst.append(weighted_matrix[:, i].max())

    # 4. Calculate Euclidean Distances
    # Distance from Best (S+) and Distance from Worst (S-)
    dist_best = np.sqrt(((weighted_matrix - ideal_best)**2).sum(axis=1))
    dist_worst = np.sqrt(((weighted_matrix - ideal_worst)**2).sum(axis=1))

    # 5. Calculate Similarity Score (Ci)
    # Ci = S- / (S+ + S-)
    scores = dist_worst / (dist_best + dist_worst)

    return scores

# --------------------------------------------------------
# EXECUTION & RESULTS
# --------------------------------------------------------
scores = topsis_method(data, weights, criteria_type)
```

```
strategies = [
    "S1: Continuous Auditing",
    "S2: TDABC",
    "S3: Smart ALM",
    "S4: XBRL",
    "S5: Fraud Detection"
]

# Sort and Print Results
ranked_indices = np.argsort(scores)[::-1]  # Sort descending

print(f"{'Rank':<5} | {'Strategy Name':<25} | {'Score (Ci)':<10}")
print("-" * 45)
for rank, idx in enumerate(ranked_indices, 1):
    print(f"{rank:<5} | {strategies[idx]:<25} | {scores[idx]:.4f}")
```

Running the above code on the research data indicates that strategy S1 (Continuous Auditing) achieves the highest similarity score (C_i), meaning that it has the shortest distance to the ideal state and the greatest distance from the worst state. This result is consistent with the findings of the qualitative section (DEMATEL), as continuous auditing functions as the primary infrastructure for transparency, which was identified as a key criterion. The use of this Python code ensures the reproducibility of the research and enables the results to be updated easily by changing the input data for different banks.

Discussion and Conclusion

The results of the present study provide robust empirical and analytical support for the argument that artificial intelligence–enabled accounting systems represent a fundamental shift in the logic of financial accounting, moving it from a static, compliance-oriented function toward a dynamic, governance-driven and decision-support ecosystem. The prioritization outcomes derived from the integrated computational intelligence and multi-criteria decision-making framework indicate that transparency, real-time auditability, data governance, and cybersecurity consistently outweigh cost considerations in the selection of advanced accounting strategies. This finding aligns with the growing body of literature emphasizing that, in digital and banking environments, the opportunity cost of insufficient transparency and weak control mechanisms far exceeds the direct financial cost of implementing advanced technologies (7, 8).

At the first analytical level, the qualitative findings derived from expert judgments confirm that traditional accounting indicators—such as historical cost and earnings per share—are no longer sufficient to capture the value creation and risk dynamics of modern financial systems. Experts emphasized the increasing importance of algorithmic processes, real-time data flows, and regulatory adaptability, which is consistent with prior conceptual and review studies highlighting the limitations of conventional accounting models in AI-driven environments (15, 16). This shift supports the argument that accounting information systems must evolve to accommodate intangible and informational assets, including data quality, algorithmic integrity, and system resilience, as central elements of financial reporting and governance (19).

The prominence of data governance quality as a foundational criterion in the fuzzy Delphi phase reinforces recent empirical evidence demonstrating that AI-driven accounting systems derive their value primarily from the integrity, structure, and governance of underlying data rather than from algorithmic sophistication alone. Studies on digital accounting and AI-enabled reporting quality similarly conclude that weak data governance undermines the reliability of automated outputs, regardless of technological advancement (3, 4). The present findings extend this line of research by demonstrating that data governance is not merely a technical prerequisite but a strategic determinant shaping the prioritization of accounting solutions.

At the second analytical level, the ANP results reveal strong nonlinear interdependencies between accounting and technical criteria, particularly between cybersecurity and reporting reliability. The high normalized weight assigned to transparency and real-time auditing indicates that continuous assurance capabilities are perceived as the primary drivers of value in intelligent accounting systems. This result is strongly aligned with empirical research on continuous auditing and AI-based anomaly detection, which shows that real-time monitoring significantly enhances audit quality and reduces both intentional and unintentional misstatements (9, 10). The feedback relationships identified through ANP further corroborate conceptual models suggesting that technical failures—such as cybersecurity breaches—directly translate into accounting and reporting failures, thereby eroding stakeholder trust (23).

The relatively lower weight assigned to implementation cost in comparison to governance-related criteria provides an important theoretical and practical insight. While cost considerations remain relevant, the findings suggest that decision-makers increasingly perceive advanced AI-based accounting systems as strategic investments rather than discretionary expenses. This perspective is consistent with studies in taxation and regulatory compliance, which report that AI-enabled systems significantly reduce long-term compliance costs by preventing errors, fraud, and regulatory penalties (11, 12). The results thus support a strategic re-framing of accounting technology investments as mechanisms for risk mitigation and value preservation rather than cost centers.

At the third analytical level, the TOPSIS and SAW rankings provide convergent evidence regarding the superiority of continuous auditing and blockchain-based accounting solutions. The dominance of continuous auditing strategies reflects their capacity to integrate transparency, automation, and real-time assurance into a single operational framework. Prior research has repeatedly emphasized that continuous auditing constitutes a cornerstone of intelligent accounting architectures by enabling proactive risk identification and ongoing validation of financial data (7, 17). The high ranking of blockchain-based accounting further reinforces arguments that distributed ledger technologies enhance trust, immutability, and traceability in financial reporting, thereby strengthening both internal control and external assurance (8).

The consistency between TOPSIS and SAW results enhances the methodological robustness of the study and confirms the reliability of the proposed prioritization framework. This convergence suggests that the rankings are not artifacts of mathematical complexity but reflect stable preference structures grounded in expert judgment and empirical logic. Similar methodological triangulation has been recommended in prior decision-science and accounting research to ensure validity and reduce model-induced bias (1, 2). The present study contributes to this methodological discourse by demonstrating the practical feasibility of embedding MCDM techniques within AI-oriented accounting research.

From a broader theoretical perspective, the findings lend strong support to the view that accounting is undergoing an epistemological transformation. Rather than serving solely as a historical record of economic events, accounting increasingly functions as an intelligent governance mechanism that integrates prediction, control, and strategic insight. This transformation is consistent with studies highlighting the convergence of financial accounting and management accounting through AI-enabled analytics and rule engines (20, 21). The present study extends this literature by providing a decision-oriented framework that operationalizes this convergence in the context of strategy selection.

Moreover, the results underscore the central role of trust and legitimacy in AI-based accounting systems. The prioritization of transparency and auditability reflects an implicit recognition that stakeholder confidence is a critical success factor in digital accounting adoption. This finding aligns with empirical evidence demonstrating that user trust mediates the relationship between AI adoption and perceived financial reporting quality (7). Similarly, research on AI-driven financial services emphasizes that technological sophistication must be complemented by robust governance and security mechanisms to sustain customer and regulator confidence (13, 14).

In summary, the discussion of results indicates that intelligent accounting strategies cannot be effectively evaluated through isolated technical or financial criteria. Instead, they must be assessed within an integrated framework that captures governance quality, transparency, security, and strategic alignment. The present study empirically demonstrates that such an integrated approach not only reflects contemporary accounting realities but also provides actionable guidance for decision-makers operating in complex digital environments (18, 23). By synthesizing insights from AI, accounting, and decision sciences, the study contributes to advancing both theory and practice in intelligent financial management.

Despite its contributions, this study is subject to several limitations that should be acknowledged. First, the expert-based nature of the qualitative and quantitative inputs may introduce contextual bias, as judgments reflect the experiences and perspectives of a specific group of specialists. Second, the decision matrix and criteria weights were developed within a particular technological and regulatory context, which may limit the direct generalizability of the results to other jurisdictions or industries. Third, the study focused on a selected set of accounting strategies and did not exhaustively cover all emerging AI-based solutions, such as advanced generative AI applications or fully autonomous accounting agents. Finally, the cross-sectional design of the analysis does not capture the dynamic evolution of AI technologies and regulatory frameworks over time.

Future research could extend the present study in several directions. Longitudinal studies could examine how the prioritization of intelligent accounting strategies evolves as AI technologies mature and regulatory environments adapt. Comparative studies across different countries, banking systems, or organizational sizes would provide deeper insights into contextual influences on strategy selection. Additionally, future research could integrate behavioral and organizational variables—such as resistance to change, ethical perceptions, or professional identity—to enrich the decision-making framework. The incorporation of advanced uncertainty modeling techniques, such as fuzzy ANP or stochastic simulations, may further enhance the robustness of strategic evaluations in highly volatile financial environments.

From a practical perspective, financial managers and policymakers should approach AI-based accounting adoption as a strategic transformation rather than a purely technical upgrade. Organizations are encouraged to prioritize transparency, real-time auditing, and data governance when selecting accounting systems, even if these solutions entail higher initial costs. Investing in interdisciplinary teams that combine accounting expertise with data analytics and information systems knowledge can facilitate effective implementation. Regulators and standard-setters may also use the insights of this study to design guidelines that promote explainable, auditable, and trustworthy AI applications in accounting. Finally, continuous training and change management initiatives are essential to ensure that human judgment and professional accountability remain integral components of intelligent accounting systems.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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