

Designing a Model for the Application of Artificial Intelligence in the Transition to Management Accounting with Emphasis on Ethical Considerations

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Abstract: The aim of this study is to design a model for the application of artificial intelligence in the transition to management accounting with emphasis on ethical considerations. With the expansion of artificial intelligence technologies, the application of these technologies in management accounting processes has created valuable opportunities for improving decision-making quality, increasing efficiency, and enhancing organizational performance. However, challenges such as privacy protection, transparency, algorithmic fairness, and accountability have further highlighted the necessity of considering ethical dimensions. In terms of purpose, the present study is applied, and in terms of method, it adopts a mixed-methods (qualitative–qualitative) approach. In the first stage, using the meta-synthesis method and a systematic analysis of previous studies, the factors affecting the application of artificial intelligence in management accounting were identified and categorized. Subsequently, in order to explain the relationships among the identified dimensions, Interpretive Structural Modeling (ISM) and MICMAC analysis were employed with the participation of experts in accounting and information technology. The findings led to the identification of 36 components classified into seven main dimensions: data ethics and privacy; algorithmic fairness and transparency; accountability and system governance; professional competence and judgment; strategic advantages and decision-making; infrastructure and implementation challenges; and organizational outcomes and social interactions. The results of Interpretive Structural Modeling indicated that dimensions related to governance, infrastructure, and ethical considerations play a driving and foundational role in the successful implementation of artificial intelligence, while the other dimensions are influenced by them. Accordingly, the realization of intelligent management accounting requires the simultaneous development of technological infrastructure, the establishment of data governance systems, the enhancement of professional competencies, and the formulation of ethical and regulatory frameworks. The findings of this study can provide a basis for policymaking, managerial decision-making, and the development of intelligent management accounting systems in organizations.

Keywords: Artificial Intelligence, Management Accounting, Ethical Considerations, Meta-Synthesis, Interpretive Structural Modeling (ISM), Data Governance

1. Introduction

Artificial intelligence (AI) has evolved from a specialized computational technology into a general-purpose organizational capability with profound implications for decision-making, information processing, control, and professional work. The historical development of AI has been characterized by successive shifts from rule-based

systems toward machine learning, data-driven prediction, natural language processing, and increasingly autonomous analytical applications, thereby expanding the range of managerial tasks that can be supported or partially automated [1, 2]. In organizational settings, AI is now applied not merely to automate routine activities but also to generate predictions, detect anomalies, process unstructured information, support complex decisions, and identify relationships that may remain hidden in conventional datasets [3, 4]. These developments are particularly consequential for accounting because accounting systems are fundamentally concerned with the collection, classification, interpretation, and communication of economic information. As data volumes increase and managerial decision environments become more dynamic, traditional accounting procedures are increasingly supplemented by intelligent information-processing capabilities that can alter both the technical infrastructure and the professional logic of accounting practice [5, 6].

Management accounting is especially exposed to this transformation because its role extends beyond historical reporting to planning, budgeting, performance evaluation, control, forecasting, strategic analysis, and decision support. Earlier developments in enterprise systems, business intelligence, and analytics already demonstrated that digital technologies can change the informational basis of managerial accounting by integrating dispersed data, improving access to real-time information, and facilitating multidimensional organizational analysis [7, 8]. Business intelligence applications have further strengthened the relationship between information systems and management accounting by improving the quality and timeliness of information used in managerial decisions [9, 10]. AI extends these capabilities by allowing management accounting systems to move from descriptive and diagnostic analysis toward predictive and prescriptive forms of analysis. Consequently, the transition toward AI-enabled management accounting should not be understood merely as the introduction of a new software tool; rather, it represents a broader transformation in the processes through which managerial information is generated, interpreted, validated, and used.

A growing body of accounting research has therefore emphasized the potential of analytics, machine learning, and AI to improve the quality of accounting information and managerial analysis. Machine-learning techniques can improve accounting estimates by detecting patterns and relationships that are difficult to capture using conventional estimation procedures [11]. Data-mining applications have similarly demonstrated considerable potential for classification, prediction, fraud detection, anomaly identification, and decision support across accounting domains [12]. In management accounting specifically, intelligent systems can improve analytical accuracy, forecasting, performance monitoring, cost analysis, and the speed with which managers receive decision-relevant information [13, 14]. Research on big data has also suggested that access to large-scale internal and external datasets can substantially alter the information environment of accountants by expanding the scope, granularity, and timeliness of analysis [15]. The strategic significance of these developments is increasingly recognized in recent research that views AI as a mechanism for shaping new informational networks and new horizons for management accounting practice [16].

The integration of AI into enterprise systems is another important aspect of this transition. Enterprise resource planning systems historically provided the integrated technological foundation through which accounting and operational information could be consolidated, whereas AI can add adaptive, predictive, and semi-autonomous capabilities to these infrastructures [17]. Such integration can potentially reduce repetitive processing, improve the quality of estimates, support continuous monitoring, and allow management accountants to redirect attention from data preparation toward interpretation and strategic advice. The use of data analytics by management accountants already indicates a shift in professional activities toward greater engagement with data extraction, modeling,

visualization, and interpretation [18]. Similarly, the increasing relevance of analytics in controllers' and management accountants' competence profiles indicates that digital transformation is changing the skills required for effective professional performance [19]. These developments imply that the future effectiveness of management accounting will depend not only on access to advanced technologies but also on the capacity of professionals to understand, critically assess, and appropriately use AI-generated outputs.

Accordingly, AI has important implications for the professional role and identity of accountants. Automation can reduce the need for some routine accounting tasks while increasing the importance of analytical interpretation, professional judgment, interdisciplinary communication, and strategic participation [20, 21]. In this context, the management accountant may progressively shift from being primarily a processor and custodian of financial information toward becoming an interpreter of algorithmically generated insights and a strategic partner in organizational decision-making. Business analytics has long been associated with the transformation of management accountants' roles, particularly by increasing their involvement in forward-looking analysis and managerial advisory activities [22]. More recent evidence concerning the adoption of AI in financial reporting likewise highlights the importance of perceived usefulness, perceived ease of use, organizational readiness, and professional acceptance in determining whether intelligent technologies become meaningfully embedded in accounting practices [23]. Thus, technological capability alone does not guarantee successful adoption; organizational, behavioral, and professional conditions are equally important.

However, the benefits of AI in accounting and management decision-making are accompanied by substantial implementation challenges. The incorporation of advanced analytics into accounting systems may require considerable investments in technical infrastructure, data architecture, training, system integration, and maintenance. Existing systems may contain fragmented, inconsistent, or low-quality data, limiting the effectiveness of AI applications even where sophisticated algorithms are available. Studies of big data in auditing have similarly identified organizational, technological, and methodological barriers that can hinder the effective use of advanced analytical tools [24]. The use of AI in accounting organizations has also been shown to depend on institutional conditions, organizational preparedness, managerial support, and the suitability of existing information systems [25]. Recent studies have further emphasized implementation challenges related to AI applications in auditing and accounting, including technical limitations, professional resistance, data reliability, and adaptation difficulties [26, 27]. These challenges indicate that the transition toward intelligent management accounting is inherently socio-technical and cannot be successfully understood through a purely technological perspective.

Another critical consideration concerns the degree of automation that should be permitted in professional accounting work. AI can assist with large-scale information processing and reduce human cognitive limitations, yet excessive automation may weaken human engagement, professional skepticism, and independent judgment. The continued relevance of human expertise is particularly important in knowledge-intensive work where contextual understanding, ethical sensitivity, and interpretation cannot be fully reduced to computational rules [28]. Research on AI in auditing similarly suggests that intelligent systems may supplement professional workforces and formalize certain procedures, but they also alter the relationship between human professionals and automated decision systems [29]. These concerns are especially salient in management accounting, where recommendations often involve uncertain strategic contexts, competing stakeholder interests, and assumptions that require interpretation rather than mechanical optimization.

The credibility of AI-generated analysis also depends on how users interpret and respond to algorithmic outputs. Even when analytics are technically accurate, users may accept or reject recommendations depending on how

results are presented, whether the reasoning behind them is understandable, and whether the output is consistent with prior beliefs or managerial expectations. Experimental research has shown that the perceived credibility of data analytics can vary according to the valence and characteristics of the advice provided [30]. Black-box analytical systems create further difficulties because users may receive recommendations without understanding the logic, assumptions, or data transformations underlying those recommendations [31]. This problem is closely related to explainability and transparency. Research in algorithmic communication has emphasized that organizations using automated systems need to provide users with sufficient information about how algorithmic processes operate and affect outputs [32]. In management accounting, this requirement is particularly important because algorithmic recommendations may influence budgeting, performance assessment, investment decisions, resource allocation, and managerial accountability.

These concerns introduce a fundamental ethical dimension into the adoption of AI. Accounting decisions frequently affect employees, investors, managers, customers, regulators, and other stakeholders. Therefore, the quality of an AI system cannot be assessed solely in terms of computational accuracy or operational efficiency. Ethical issues may arise from privacy violations, unauthorized secondary use of data, biased training datasets, opaque decision processes, unequal treatment, responsibility for system errors, and the potential displacement of human judgment. The ethical implications of AI in auditing have already been examined in terms of independence, responsibility, transparency, fairness, and professional judgment [33]. Research focused more directly on managerial accounting similarly demonstrates that AI can generate ethical concerns when algorithmic outputs affect organizational decisions and stakeholder interests [34, 35]. These concerns are not peripheral to technological adoption; rather, they influence whether intelligent systems can be regarded as legitimate, trustworthy, and professionally acceptable.

The ethical challenges associated with AI also build upon a longer tradition of research on ethics in accounting information systems. Previous scholarship has shown that accounting information systems involve ethical questions related to control, responsibility, information use, professional conduct, and the social consequences of technology [36]. Subsequent work has argued that ethics in accounting information systems constitutes a distinct and increasingly important domain, particularly as digital systems acquire greater influence over professional decisions [37]. The growing importance of ethics in technologically mediated accounting has also generated debate regarding how ethical research is framed, disseminated, and institutionalized within the accounting information systems literature [38, 39]. The transition toward AI-enabled management accounting therefore occurs within an established but rapidly expanding ethical research context.

Algorithmic fairness is one of the most significant ethical issues in this context. AI systems learn from historical data, and if these data reflect organizational inequalities, biased judgments, or incomplete representations, the resulting models may reproduce or intensify such problems. Ethical risks may also emerge when algorithms optimize narrowly defined performance objectives without considering broader stakeholder consequences. Research on corporate responsibility in relation to AI emphasizes that organizations remain responsible for the social and ethical consequences of algorithmic systems, even when decisions are partially automated [40]. In the accounting context, this means that responsibility cannot simply be transferred to software developers or technical systems. Managers, management accountants, system designers, and organizational governance bodies may all share responsibility for defining objectives, choosing data, evaluating outputs, and responding to identified risks. Ethical decision-making in accounting and auditing therefore increasingly requires explicit attention to the relationship between technological capability and professional responsibility [41].

Privacy and data governance are similarly central because AI applications depend heavily on extensive data collection and integration. Management accounting systems may incorporate financial, operational, behavioral, employee, customer, and external market information. The value of such integrated data is significant, but so is the potential for misuse, unauthorized access, or application beyond the purpose for which the information was originally collected. The broader development of AI legislation and regulation reflects growing concern over transparency, privacy, accountability, and human oversight [42, 43]. These regulatory developments reinforce the need for organizations to treat data governance as an integral element of AI implementation rather than as a secondary technical concern.

A related ethical challenge is the tension between system efficiency and human autonomy. AI may improve consistency and reduce some forms of human error, but organizational dependence on algorithmic recommendations can also reduce professional skepticism and create automation bias. In accounting environments, excessive reliance on AI may encourage users to accept outputs without sufficient verification, particularly when systems are perceived as technically sophisticated. Ethical management accounting therefore requires a balance between technological assistance and meaningful human oversight. This balance is particularly important where decisions are ambiguous, value-laden, or involve trade-offs that cannot be fully captured by quantitative models. Research on the digitization of knowledge-intensive services likewise indicates that technology creates value most effectively when combined with human expertise and collaborative processes rather than treated as a complete substitute for professional agency [44].

The benefits of AI nevertheless remain substantial. AI-supported analysis can enhance the precision of forecasting, identify unusual transactions, support fraud and error detection, automate recurring analyses, improve cost and performance measurement, and facilitate the processing of very large datasets. Research on emerging accounting technologies has emphasized the growing importance of automated and technology-assisted procedures for monitoring and assurance [45]. Predictive algorithms have also been applied to financial distress and bankruptcy forecasting using combinations of accounting and macroeconomic variables [46]. Intelligent analysis can therefore contribute to both operational efficiency and risk management. Furthermore, performance measurement systems increasingly rely on multidimensional and data-intensive approaches, suggesting that intelligent technologies may enhance managers' ability to assess complex organizational outcomes [47]. These capabilities collectively suggest that AI can strengthen the strategic relevance of management accounting when technological outputs are appropriately governed and interpreted.

At the same time, the successful realization of these advantages requires attention to organizational trust and legitimacy. Management accountants and other decision-makers must have sufficient confidence in AI systems to use their outputs, yet this trust should remain calibrated rather than unconditional. Transparent logic, reliable data, understandable explanations, professional competence, and clear lines of accountability are therefore essential for developing appropriate trust. The problem is not simply whether AI systems are technically reliable, but whether users can understand their limitations and whether organizational governance mechanisms can identify and correct failures. The ethical and managerial consequences of AI thus emerge through interaction among technological infrastructure, professional competence, data quality, governance, and organizational culture.

These considerations indicate that research on AI in management accounting should move beyond fragmented examinations of individual benefits or individual risks. Much of the existing literature has focused separately on technological capabilities, analytics, professional transformation, implementation barriers, or ethical challenges. Yet the transition toward AI-enabled management accounting represents a multidimensional system in which these

factors are interdependent. Technical infrastructure shapes the feasibility of intelligent applications; governance influences accountability and control; ethical data practices affect legitimacy; professional competence affects interpretation; algorithmic fairness influences trust; and strategic benefits depend on the combined functioning of these conditions. Accordingly, an integrated model is needed to explain not only which factors are relevant but also how they are structurally related and which factors function as fundamental drivers rather than dependent outcomes.

The need for such integration is reinforced by the increasing complexity of AI-supported managerial decision environments. As intelligent systems become more embedded in planning, forecasting, control, and performance management, organizations require frameworks that can simultaneously account for technological readiness, ethical safeguards, professional capabilities, managerial benefits, and organizational consequences. Without such a framework, organizations may pursue efficiency gains while underestimating risks involving bias, privacy, accountability, employee resistance, and professional dependence. Conversely, an excessively risk-oriented approach may prevent organizations from realizing legitimate improvements in analytical quality, cost efficiency, fraud detection, decision support, and strategic responsiveness. The central challenge is therefore to identify a balanced architecture in which AI contributes to management accounting without undermining professional responsibility, ethical principles, or organizational legitimacy.

Accordingly, the aim of this study is to design a model for the application of artificial intelligence in the transition to management accounting with emphasis on ethical considerations.

2. Methods and Materials

In terms of purpose, the methodology of this study is applied, and in terms of approach, it is mixed-methods (qualitative–quantitative). In the qualitative phase, the factors affecting the application of artificial intelligence in the transition to management accounting with emphasis on ethical considerations were identified and explained. In the quantitative phase, the relationships among these factors were analyzed and modeled using Interpretive Structural Modeling (ISM). To identify the influential factors, a systematic literature analysis method was employed, whereby scientific articles, credible studies, specialized documents, and related sources were purposefully reviewed and analyzed. Moreover, given the exploratory nature of the study, purposive sampling was used in the qualitative phase, and the required data were collected through the review and analysis of relevant sources. To assess the validity of the qualitative findings, content validity was examined using the Content Validity Ratio (CVR). In addition, the reliability of the coding process was assessed using Cohen's kappa coefficient. The Cohen's kappa coefficient was calculated as 0.90, indicating a very high level of agreement between coders and consequently confirming the reliability and stability of the coding process and the study findings. The data coding process was conducted using MAXQDA 2020 software. As a result of the systematic data analysis, seven main categories were identified and extracted as factors affecting the application of artificial intelligence in the transition to management accounting with emphasis on ethical considerations. Subsequently, these factors were analyzed using Interpretive Structural Modeling in terms of hierarchical levels, interrelationships, driving power, and dependence, and the final research model was developed.

In the next stage of the study, the factors affecting the application of artificial intelligence in the transition to management accounting with emphasis on ethical considerations were modeled using Interpretive Structural Modeling (ISM). The expert population at this stage consisted of theoretical experts (university faculty members) and practical experts (specialists and managers in the capital market). The research sample was selected using

purposive sampling, and ultimately, 18 experts with specialized knowledge and relevant experience in the fields of management accounting, artificial intelligence, and the capital market participated in the study. The required data were collected through a pairwise comparison questionnaire. In this questionnaire, the experts evaluated the relationships among the identified factors based on pairwise comparison logic and the degree of influence of each factor on the other factors. To ensure the validity of the data collection instrument, the content validity method was employed. For this purpose, after extracting the factors affecting the application of artificial intelligence in the transition to management accounting with emphasis on ethical considerations, the Q-Sort method was used to examine the degree of expert agreement regarding the relevance and importance of the factors. In implementing the Q-Sort method, each identified factor was recorded on a separate card and provided to the experts. In the first stage, the experts classified the factors into two groups based on their degree of importance: important and less important. These two groups were then subdivided into four categories: very important, important, less important, and very unimportant. Subsequently, to enhance the precision of expert judgment, a moderately important category was added to the scale. Ultimately, the experts determined the importance of each factor by distributing the factors across five value levels. After completion of the classification process, the factors placed in the very important and important groups were entered into the Interpretive Structural Modeling stage as the final factors.

Subsequently, based on expert judgments, the Structural Self-Interaction Matrix (SSIM) was developed and converted into the initial reachability matrix. After applying the principle of transitivity, the final reachability matrix was obtained. The hierarchical relationships among the factors were then determined through the level-partitioning process, and finally, the Interpretive Structural Model of the factors affecting the application of artificial intelligence in the transition to management accounting with emphasis on ethical considerations was developed and analyzed (Cerf and Sherman, 2013). The results of the analysis of data collected from seven experts confirmed the importance of the identified factors affecting the application of artificial intelligence in the transition to management accounting with emphasis on ethical considerations. To assess reliability, the test–retest method was employed, and the questionnaire was redistributed three weeks later to university professors and a number of experienced and knowledgeable experts in the research field. The correlation between the responses was estimated at 80%, confirming the reliability of the questionnaire.

Table 1. Demographic Characteristics of the Interviewees

Gender	Education	Occupation	Work Experience (Years)	Gender	Education	Occupation	Work Experience
Male	PhD	Faculty Member	14	Male	PhD	Faculty Member	13
Female	PhD	Faculty Member	9	Male	PhD	Faculty Member	8
Male	Master's Degree	Senior Manager	10	Male	PhD	Faculty Member	11
Female	PhD	Faculty Member	11	Male	PhD	Faculty Member	17
Male	PhD	Faculty Member	14	Male	PhD	Faculty Member	6
Male	Master's Degree	Senior Manager	18	Male	PhD	Senior Manager	14
Male	PhD	Faculty Member	9	Female	PhD	Faculty Member	11
Female	PhD	Faculty Member	10	Male	Master's Degree	Manager	16
Male	PhD	Faculty Member	13	Male	PhD	Faculty Member	12

The following table presents the demographic characteristics of the experts participating in the interviews by gender, age, education, and work experience.

Table 2. Demographic Characteristics of the Experts

Demographic Characteristic	Category	Frequency	Percentage
Gender	Male	14	77.8
	Female	4	22.2
Age	20–30 years	1	5.6
	31–40 years	9	50.0
	More than 41 years	8	44.4
Education	Master's Degree	3	16.7
	PhD	15	83.3
Work Experience	0–10 years	6	33.2
	11–15 years	9	50.0
	More than 15 years	3	16.8

3. Findings and Results

Extensive analysis was conducted on documents and scientific sources related to the application of artificial intelligence (AI) in the transition to management accounting, with particular emphasis on ethical considerations. The qualitative analysis focused on identifying the ethical challenges, implementation requirements, organizational consequences, and potential advantages associated with the integration of AI into management accounting systems.

The factors associated with the application of AI in the transition to management accounting were identified through five stages: (1) defining the scope of the study, (2) conducting a systematic review of the theoretical literature, (3) searching for and selecting relevant studies, (4) extracting information from the selected studies, and (5) extracting and categorizing codes and themes. The literature review covered peer-reviewed articles and authoritative scientific reports indexed in major international databases, including Web of Science, Scopus, ScienceDirect, and Google Scholar.

The main Persian and English keywords and Boolean search strategies employed to retrieve the relevant literature are presented in Table 3.

Table 3. General Keywords and Search Strategy Used in Scientific Databases

Language	Search Strategy
Persian	("هوش مصنوعی" OR "AI" OR "یادگیری ماشین") AND ("حسابداری مدیریتی" OR "حسابداری مدیریت") AND ("چالشهای اخلاقی" OR "مزیتها") AND "گذار"
English	("Artificial Intelligence" OR "AI" OR "Machine Learning") AND ("Management Accounting" OR "Managerial Accounting") AND ("Ethical Challenges" OR "Advantages") AND "Transition"

The retrieved studies were screened in several stages based on their titles, abstracts, document types, and substantive relevance to the research topic. Screening was conducted sequentially according to publication language, document type, relevance to the research domain, and abstract content. Each article was coded separately.

A total of 76 scientific articles were initially identified. Of these, 12 studies were excluded because they were not published in English, 13 were excluded because their subject matter or abstracts were not sufficiently relevant to the study, and 22 were excluded during document-type screening and the restriction to Article and Review documents. Accordingly, 29 sources and documents remained for final analysis.

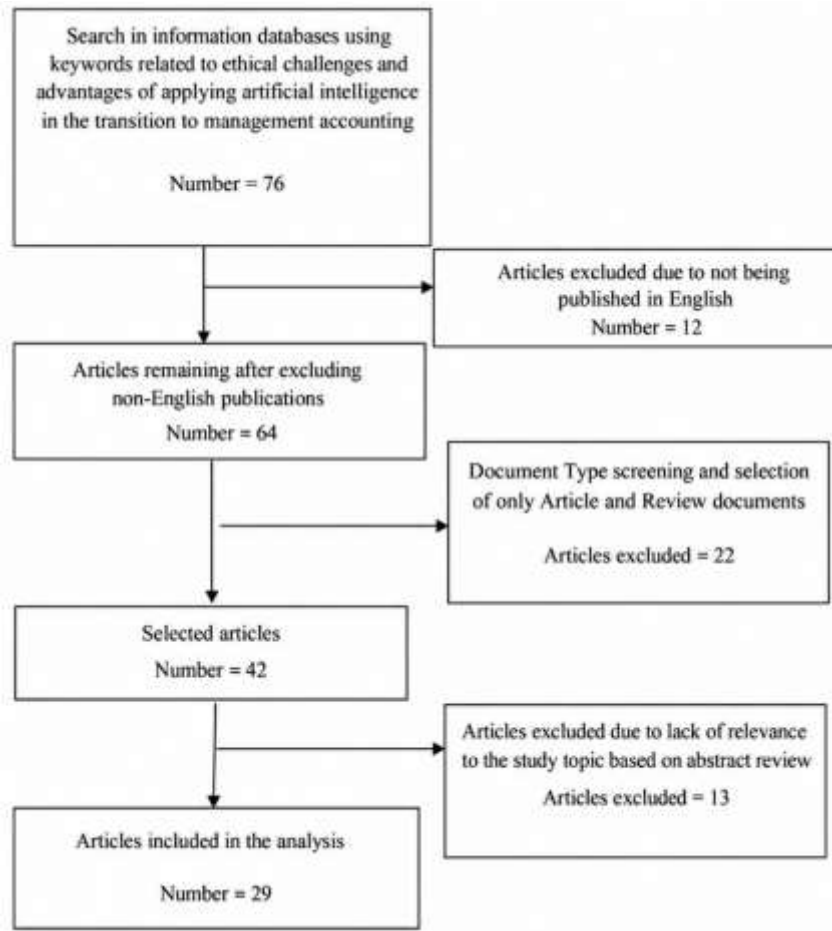


Figure 1. Article Selection and Screening Flowchart

Following the initial screening based on formal criteria, including English-language publication, Article or Review document type, and removal of duplicate or ineligible records, the remaining studies underwent content-based screening. At this stage, the abstracts and, where necessary, full texts were assessed according to three principal inclusion criteria. First, the article had to address both AI/machine learning and accounting or management accounting. Second, it had to discuss at least one of the following: ethical considerations, implementation challenges, or advantages associated with AI applications. Third, it had to have been published between 2001 and 2025.

The exclusion criteria comprised studies that focused exclusively on the technical or algorithmic aspects of AI, such as improvements in machine-learning model accuracy, without addressing accounting applications or ethical considerations; studies that discussed AI in business only in general terms without a direct relationship to management accounting; and studies for which the full text was unavailable. The screening procedure was independently conducted by two researchers, and disagreements were resolved through discussion and consensus. The final screening outcome is represented in the PRISMA flow diagram shown in Figure 1.

Following detailed review, organization, and coding of the selected literature, 36 statements or concepts were identified. Concepts that appeared more frequently in the literature or were discussed from multiple conceptual perspectives were retained as influential indicators.

In the fourth stage, the selected studies were categorized according to the factors, barriers, ethical considerations, and outcomes associated with AI adoption in management accounting. The 36 components identified through the systematic content analysis are presented in Table 4.

Table 4. Identified Components, Indicators, and Consequences of the Ethical Challenges and Advantages of AI Application in the Transition to Management Accounting

No.	Key Component	Extracted Indicators	Sources
1	Data security	Protection of financial data; prevention of information leakage; database security; access control	Kaplan and Haenlein (2020); Munoko et al. (2020); Marques et al. (2023); Zhang et al. (2023)
2	Privacy	Prevention of employee and stakeholder privacy violations; restriction of secondary data use; confidentiality	European Group on Ethics in Science and New Technologies (2018); China AI Governance Committee (2019); Warren (2015); Azarsaeed and Rostami (2023)
3	Data misuse	Unauthorized data use; unlawful reuse; data manipulation; use beyond the original purpose	China AI Governance Committee (2019); Alles (2020); Javadi (2023)
4	Algorithmic transparency	Explainability of results; clarity of decision logic; process traceability; model comprehensibility	Kaplan and Haenlein (2019); Ashok and Madan (2022); Marques et al. (2023)
5	Trust in AI	Acceptance of system outputs; confidence in analyses; legitimacy of AI-based decisions; organizational trust	Munoko et al. (2020); Zhang (2025); Zhang et al. (2023)
6	Expectation gap	Discrepancy between user expectations and actual system performance; unfulfilled technological promises; user dissatisfaction	Munoko et al. (2020); Li et al. (2020); Zhang et al. (2023)
7	Accountability	Identification of responsibility for errors; answerability for decisions; allocation of responsibility among developers, managers, and users	Dillard et al. (2005); Davern et al. (2019); Munoko et al. (2020)
8	Shared responsibility	Allocation of responsibility among developers, managers, management accountants, and regulators	China AI Governance Committee (2019); Manweno (2005); Dillard and Yuthas (2002)
9	Algorithmic bias	Discrimination arising from training data; transfer of prejudices to models; unfair outcomes	European Group on Ethics in Science and New Technologies (2018); Guragai et al. (2017); Marques et al. (2023)
10	Justice and fairness	Equitable distribution of benefits; nondiscrimination; respect for stakeholder rights; fair decision-making	European Group on Ethics in Science and New Technologies (2018); China AI Governance Committee (2019); Villegas, Gálvez, and Martín (2022)
11	Human autonomy	Preservation of human decision-making authority; prevention of complete machine dependence; possibility of human intervention	European Group on Ethics in Science and New Technologies (2018); Kleindorfer et al. (1993); Alles (2020)
12	System controllability	Ability to stop, modify, and supervise system operations; intervention under critical conditions	China AI Governance Committee (2019); Ashok and Madan (2022)
13	Reliability	Performance stability; consistency of results; analytical validity; continuous dependable operation	Richardson (2018); Boulay et al. (2021); Marques et al. (2023)
14	Analytical accuracy and precision	Reduction of human error; improved forecasting accuracy; accurate reporting; enhanced output quality	Amani and Fadlalla (2017); Boulay et al. (2021); Davenport and Ronanki (2018)
15	Users' technical competence	Knowledge of system use; understanding of algorithms; ability to interpret outputs; AI literacy	Oesterreich and Teuteberg (2023); Sutton et al. (2022); Rezaei (2023)
16	Training and retraining	Preimplementation training; continuous learning; development of analytical and technological skills	Javadi (2023); Oesterreich and Teuteberg (2023); Rezaei (2023)
17	Professional judgment	Preservation of human analytical capabilities; complementary use of AI; interpretation of outputs through professional expertise	Granlund (2011); Sutton et al. (2022); Quattrone (2016)

18	Erosion of professional skepticism	Reduced professional skepticism; unquestioning acceptance of outputs; decline in critical thinking	Alles (2020a); Munoko et al. (2020)
19	Overreliance on AI	Excessive user dependence; reduced independent analysis; complete substitution of human decision-making	Munoko et al. (2020); Azarsaeed and Rostami (2023)
20	Distortion of results	Misleading outputs; misinterpretation of data; biased presentation of reports	Guragai et al. (2017); Martín and Villegas-Galaviz (2022)
21	Quality of managerial decision-making	Improved diagnostic and predictive decisions; deeper analysis; improved quality of managerial choices	Röglinger (2020); Chen (2021); Marques and Bao (2023)
22	Operational speed and efficiency	Automation of activities; time savings; increased productivity; reduction of repetitive work	Davenport and Ronanki (2018); Aktürk (2021); Zhang (2025)
23	Cost reduction	Lower labor costs; reduced processing and control costs; operational savings	Aktürk (2021); Li et al. (2020)
24	Improved financial forecasting	More accurate performance forecasting; intelligent budgeting; trend and risk analysis	Boulay et al. (2021); Richins et al. (2017); Vaghefi (2019)
25	Improved performance measurement	More accurate measurement of indicators; continuous performance monitoring; intelligent managerial dashboards	Röglinger (2020); Richardson (2018); Chen (2021)
26	Support for management control	Strengthening internal control; intelligent monitoring; detection of deviations and anomalies	Richardson (2018); Warren (2015); Brands and Holtzblatt (2015)
27	Data integration	Integration of internal and external data; connection of data sources; information consistency	Richardson (2018); Appelbaum (2017); Marques et al. (2023)
28	Big-data analytics	Processing massive volumes of data; identification of hidden patterns; data-driven decision-making	Kaplan and Haenlein (2019); Appelbaum (2017); Arab, Salehi, et al. (2025)
29	Fraud and error detection	Detection of anomalies; identification of financial fraud; rapid alerts; monitoring of abnormal behavior	Amani and Fadlalla (2017); Heydariyousef, Piri, and Chalaki (2025); Rabiei (2024)
30	Compatibility with existing systems	Compatibility with ERP and accounting systems; technical integration challenges; infrastructural coordination	Dillard et al. (2005); Marques et al. (2023); Bagherian et al. (2023)
31	Implementation costs	High initial investment; maintenance costs; training and infrastructure development costs	Li et al. (2020); Zhang et al. (2023)
32	Employee resistance	Concerns regarding change; fear of job displacement; resistance to technology adoption	Li et al. (2020); Rezaei (2023); Javadi (2023)
33	Workplace isolation	Reduced face-to-face interaction; online performance of tasks; weakening of interpersonal communication	Warren (2015); Rogers and Gago (2003)
34	Changing role of management accountants	Transition from data processing to strategic advisory roles; greater emphasis on analysis and interpretation	Quattrone (2016); Richins et al. (2017); Rezaei (2023)
35	Governance and regulation	Development of ethical codes; behavioral standards; implementation and supervisory guidelines	Guragai et al. (2017); Sheikholeslami (2018); Azarsaeed and Rostami (2023)
36	Stakeholder interests and ethical conflicts	Balancing the interests of different groups; conflicting ethical perspectives; consideration of vulnerable groups	Rogers and Gago (2003); Röglinger et al. (2020); Villegas, Gálvez, and Martín (2022)

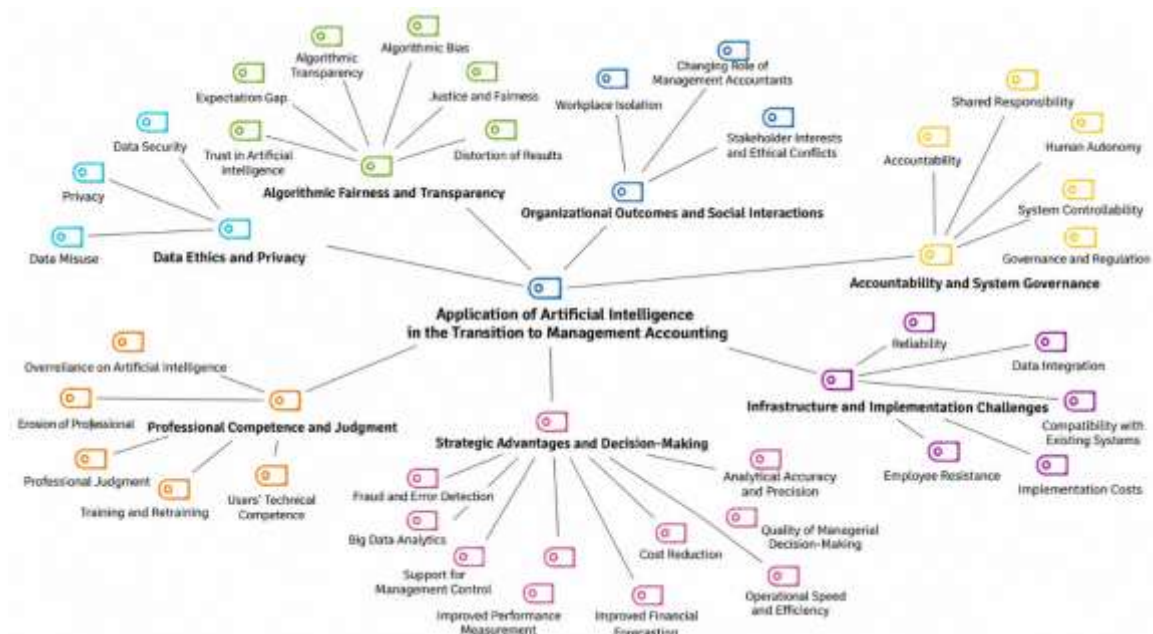
In the fifth stage of the content analysis, the extracted codes were decomposed, compared, and integrated according to their conceptual similarities. The 36 key components were ultimately classified into seven principal dimensions. This classification demonstrates that the challenges and benefits associated with AI in management accounting are not confined to technical issues, but also encompass ethical, professional, organizational, and strategic domains.

Table 5. Classification of the 36 Key Components into Seven Main Dimensions

No.	Main Dimension	Key Components
1	Data ethics and privacy	Data security; privacy; data misuse
2	Algorithmic fairness and transparency	Algorithmic transparency; trust in AI; expectation gap; algorithmic bias; justice and fairness; distortion of results
3	Accountability and system governance	Accountability; shared responsibility; human autonomy; system controllability; governance and regulation
4	Professional competence and judgment	Users' technical competence; training and retraining; professional judgment; erosion of professional skepticism; overreliance on AI
5	Strategic advantages and decision-making	Analytical accuracy and precision; quality of managerial decision-making; operational speed and efficiency; cost reduction; improved financial forecasting; improved performance measurement; support for management control; big-data analytics; fraud and error detection
6	Infrastructure and implementation challenges	Reliability; data integration; compatibility with existing systems; implementation costs; employee resistance
7	Organizational outcomes and social interactions	Workplace isolation; changing role of management accountants; stakeholder interests and ethical conflicts

Following axial coding and thematic analysis, conceptually similar codes were grouped together. The resulting seven axial dimensions were data ethics and privacy, algorithmic fairness and transparency, accountability and system governance, professional competence and judgment, strategic advantages and decision-making, infrastructure and implementation challenges, and organizational outcomes and social interactions. As shown in Table 5, these dimensions provide a structured framework for simultaneously understanding both the ethical challenges and the potential advantages of AI in the transition toward contemporary management accounting.

The greatest concentration of components was observed in the dimensions of strategic advantages and decision-making and algorithmic fairness and transparency. This finding indicates, on the one hand, that AI possesses substantial capacity to improve decision quality and efficiency in management accounting and, on the other hand, that neglecting transparency, fairness, and ethical control may generate substantial risks for organizations and their stakeholders.

**Figure 2. Schematic Output of the MAXQDA Analysis**

Interpretive Structural Modeling (ISM) was employed to develop the initial structural model of AI application in the transition to management accounting with emphasis on ethical considerations. ISM is an exploratory modeling technique widely used in management research. Its initial conceptualization is attributed to Warfield (1974), and it was subsequently introduced and further developed by Sage (1977). The approach enables experts to represent complex relationships among numerous elements within a complex decision-making environment.

ISM provides a systematic mechanism for structuring and directing complex relationships among constructs. By examining the influence of one construct on another, the approach identifies the sequence and direction of relationships within a system and thereby reduces the complexity of interrelationships among constructs (Azar et al., 2019).

The ISM procedure begins by developing a list of criteria involved in the problem and defining each criterion or subcriterion as e_i , where $i = 1, 2, \dots, n$ (Li et al., 2010). A relational matrix is then constructed to represent relationships among the criteria and subcriteria based on expert judgments (Swaral et al., 2011). Experts answer questions such as whether variable e_i influences variable e_j . If the answer is affirmative, $r_{ij} = 1$; otherwise, $r_{ij} = 0$.

The general relational matrix may be represented as:

$$S = [r_{ij}], i = 1, 2, \dots, n; j = 1, 2, \dots, n$$

where e_i denotes the i th component in the system, r_{ij} represents the relationship between components i and j , and S denotes the relational matrix (Huang et al., 2005).

The reachability matrix is then obtained as follows:

$$\begin{aligned} N &= S + I \\ N^* &= N^k = N^{k+1}, k > 1 \end{aligned}$$

where I denotes the identity matrix, k represents matrix powers, and N^* denotes the final reachability matrix.

The reachability and antecedent sets can subsequently be obtained using:

$$\begin{aligned} A(t_i) &= \{t_j \mid m'_{ij} = 1\} \\ B(t_i) &= \{t_j \mid m'_{ji} = 1\} \end{aligned}$$

where m_{ij} represents the value in the i th row and j th column. The level of each component is determined when:

$$B(t_i) \cap A(t_i) = B(t_i)$$

In practical terms, the procedure begins with the development of the Structural Self-Interaction Matrix (SSIM), in which the study components appear in both rows and columns and their relationships are evaluated on the basis of expert judgments.

For ISM analysis, the seven dimensions confirmed through the qualitative analysis were assigned abbreviated codes. Eighteen theoretical experts, including university faculty members, and practical experts, including specialists and capital-market managers, participated in this stage and completed the matrix questionnaire concerning the interrelationships among the dimensions.

Table 6. Main Dimensions and Abbreviated Codes Used in the ISM Analysis

Code	Main Dimension
X1	Data ethics and privacy
X2	Algorithmic fairness and transparency
X3	Accountability and system governance

X4	Professional competence and judgment
X5	Strategic advantages and decision-making
X6	Infrastructure and implementation challenges
X7	Organizational outcomes and social interactions

In the second stage, the SSIM was constructed to determine the direction of causal influence among the dimensions. The matrix contains the study variables in both its rows and columns, and pairwise relationships are specified using conventional ISM symbols (Tizroo, 2010; Jitesh Thakkar et al., 2017).

In each pairwise comparison, the experts used the symbols V, A, X, and O. V indicates that variable *i* influences variable *j*; A indicates that variable *j* influences variable *i*; X indicates a bidirectional relationship; and O indicates the absence of a relationship.

The resulting SSIM is presented in Table 7.

Table 7. Structural Self-Interaction Matrix for the Dimensions of AI Application in the Transition to Management Accounting

	X1	X2	X3	X4	X5	X6	X7
X1	–	V	A	O	O	A	V
X2		–	A	A	V	O	V
X3			–	V	O	A	O
X4				–	V	A	V
X5					–	A	V
X6						–	O
X7							–

The conceptual symbols were converted into binary values to construct the initial reachability matrix. Specifically, for **V**, the corresponding cell was assigned 1 and its symmetric cell 0; for **A**, the corresponding cell was assigned 0 and its symmetric cell 1; for **X**, both cells were assigned 1; and for **O**, both cells were assigned 0. The elements on the principal diagonal were assigned a value of 1.

The initial reachability matrix was derived by converting the SSIM into a binary matrix. Subsequently, transitivity was examined. Under the transitivity principle, if X_1 influences X_2 , and X_2 influences X_3 , then X_1 is also assumed to influence X_3 . Application of this principle generated the final reachability matrix.

Because both matrices are essential for evaluating the structural relationships, they are reported together in Table 8.

Table 8. Initial and Final Reachability Matrices

Panel A. Initial Reachability Matrix

	X1	X2	X3	X4	X5	X6	X7
X1	1	1	0	0	0	0	1
X2	0	1	0	0	1	0	1
X3	1	1	1	1	0	0	0
X4	0	1	0	1	1	0	1
X5	0	0	0	0	1	0	1
X6	0	0	1	1	1	1	0
X7	0	0	0	0	0	0	1

Panel B. Final Reachability Matrix and Driving/Dependence Powers

	X1	X2	X3	X4	X5	X6	X7	Driving Power
X1	1	1	0	0	1	0	1	4

X2	0	1	0	0	1	0	1	3
X3	1	1	1	1	1	0	1	6
X4	0	1	0	1	1	0	1	4
X5	0	0	0	0	1	0	1	2
X6	1	1	1	1	1	1	1	7
X7	0	0	0	0	0	0	1	1
Dependence Power	3	5	2	3	6	1	7	

The final reachability matrix clearly demonstrates the interrelationships and influence patterns among the dimensions. Driving power represents the number of elements influenced by a given dimension, whereas dependence power represents the number of elements influencing that dimension. These two indices were subsequently used in the MICMAC analysis.

X6 exhibited the greatest driving power, with a score of 7 and a dependence score of only 1. X3 ranked next in driving power, with a score of 6 and dependence of 2. In contrast, X7 had the lowest driving power, 1, and the highest dependence, 7. X5 also showed relatively high dependence, with a value of 6, but relatively weak driving power, with a value of 2.

To determine hierarchical relationships among the dimensions, the reachability set and antecedent set were extracted for each dimension from the final reachability matrix. The reachability set comprises the focal dimension and the dimensions that it can influence, whereas the antecedent set comprises the focal dimension and all dimensions capable of influencing it.

The intersection of the two sets was subsequently calculated. A dimension was assigned to the current level when its reachability set was identical to the intersection set. Once a level was identified, its dimensions were removed, and the procedure was repeated until all dimensions had been assigned to hierarchical levels.

The complete level-partitioning process is summarized in Table 9.

Table 9. ISM Level Partitioning of the Dimensions

Iteration	Code	Antecedent Set	Reachability Set	Intersection Set	Assigned Level
1	X1	1, 3, 6	1, 2, 5, 7	1	–
1	X2	1, 2, 3, 4, 6	2, 7	2	–
1	X3	3, 6	1, 2, 3, 4, 5, 7	3	–
1	X4	3, 4, 6	2, 4, 5, 7	4	–
1	X5	1, 2, 3, 4, 5, 6	5, 7	5	–
1	X6	6	1, 2, 3, 4, 5, 6, 7	6	–
1	X7	1, 2, 3, 4, 5, 6, 7	7	7	Level 1
2	X1	1, 3, 6	1, 2, 5	1	–
2	X2	1, 2, 3, 4, 6	2	2	Level 2
2	X3	3, 6	1, 2, 3, 4, 5	3	–
2	X4	3, 4, 6	2, 4, 5	4	–
2	X5	1, 2, 3, 4, 5, 6	5	5	Level 2
2	X6	6	1, 2, 3, 4, 5, 6	6	–
3	X1	1, 3, 6	1	1	Level 3
3	X3	3, 6	1, 3, 4	3	–
3	X4	3, 4, 6	4	4	Level 3
3	X6	6	1, 3, 4, 6	6	–
4	X3	3, 6	3	3	Level 4
4	X6	6	3, 6	6	Level 5

During the first iteration, X7 was identified as the Level 1 dimension because its reachability and intersection sets were identical. The remaining dimensions could not be eliminated at this stage.

After removal of X7, the second iteration showed that X2 and X5 had identical reachability and intersection sets and were therefore assigned to Level 2.

In the third iteration, following removal of X2 and X5, X1 and X4 were identified as Level 3 dimensions.

Finally, after removal of X1 and X4, X3 was assigned to Level 4 and X6 to Level 5.

Thus, the final hierarchical structure comprised five levels: X7 at Level 1; X2 and X5 at Level 2; X1 and X4 at Level 3; X3 at Level 4; and X6 at Level 5.

Based on the final reachability matrix and the results of level partitioning, the seven dimensions were arranged into a five-level structural hierarchy. In ISM interpretation, the lower structural layers constitute the more fundamental driving conditions, whereas the upper layers represent increasingly dependent outcomes. Accordingly, although X6 was designated as **Level 5** during the iterative partitioning procedure, it represents the foundational or bottom layer of the structural model. X7, designated as **Level 1**, represents the most dependent outcome layer.

Infrastructure and implementation challenges (X6) therefore constitute the most fundamental driver of the model. Accountability and system governance (X3) occupy the next foundational layer, followed by data ethics and privacy (X1) and professional competence and judgment (X4). Algorithmic fairness and transparency (X2) and strategic advantages and decision-making (X5) constitute the next outcome-oriented layer, while organizational outcomes and social interactions (X7) represent the final and most dependent outcome.

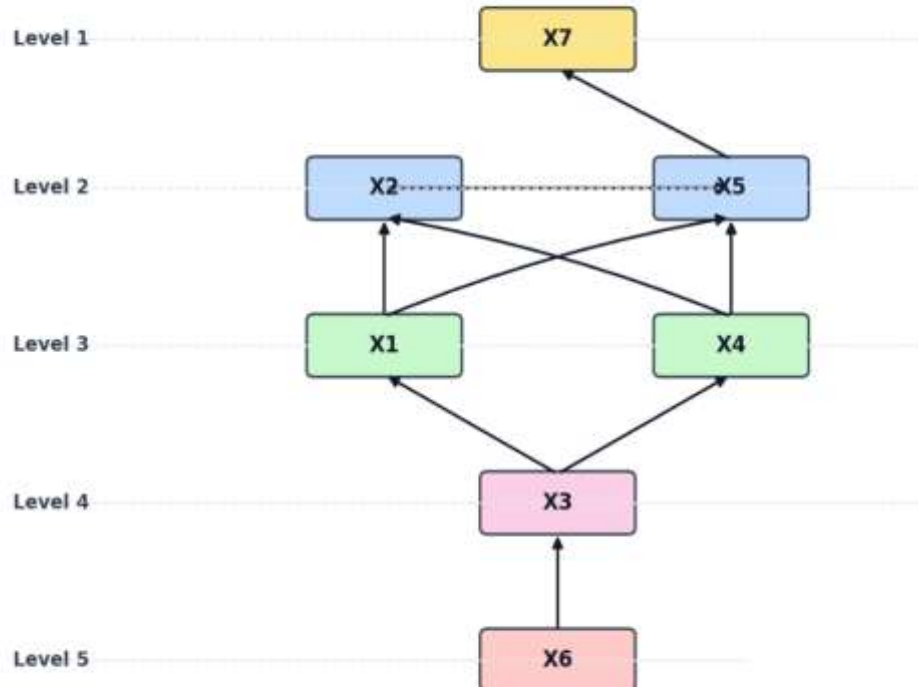


Figure 3. Interpretive Structural Model of the Factors Affecting AI Application in the Transition to Management Accounting with Emphasis on Ethical Considerations

Following development of the ISM model, the seven dimensions were evaluated using MICMAC analysis based on their driving power and dependence power. MICMAC analysis facilitates further interpretation of each variable according to the number of variables it influences and the number of variables by which it is influenced.

The variables can generally be classified into four groups: autonomous variables, characterized by low driving power and low dependence; dependent variables, characterized by weak driving power and high dependence; linkage variables, characterized by both high driving power and high dependence; and independent or driving variables, characterized by high driving power and low dependence.

	Independent					Linkage			
7			X6						
6				X3					
5									
4					X1, X4				
3						X2			
2							X5		
1	Autonomous							X7	Dependent
0			1	2	3	4	5	6	7

Figure 4. MICMAC Analytical Matrix of the Factors Affecting AI Application in the Transition to Management Accounting with Emphasis on Ethical Considerations

Data ethics and privacy (X1) had a driving power of 4 and a dependence power of 3 and therefore occupied a relatively influential position with limited dependence. This result indicates that X1 is not merely a final consequence of the model; rather, it can influence several other dimensions, particularly algorithmic fairness and transparency, strategic decision-related advantages, and organizational outcomes. Its comparatively limited dependence also suggests that this dimension is primarily shaped by more fundamental factors such as infrastructure and system governance. Once established, however, it assumes a directional role in the upper layers of the model. X1 can therefore be interpreted as an influential intermediate variable connecting governance-related foundations to strategic and social outcomes.

Algorithmic fairness and transparency (X2) had a driving power of 3 and a dependence power of 5, placing it among the relatively dependent variables. This finding indicates that X2 functions more as a consequence of infrastructural, governance-related, ethical, and professional conditions than as a fundamental driver. In other words, meaningful algorithmic fairness and transparency can be achieved only when prerequisites such as appropriate infrastructure, system accountability, data ethics, and professional competence are already in place. Nevertheless, X2 is not completely passive because it can still influence strategic advantages and social outcomes. It can therefore be regarded as an important dependent variable that converts foundational requirements into legitimate and defensible organizational outcomes.

Accountability and system governance (X3) had a driving power of 6 and a dependence power of 2, making it one of the most influential driving variables in the model. This position demonstrates that X3 exerts broad influence on most dimensions while being affected by relatively few variables, particularly infrastructure and implementation conditions. From an interpretive perspective, governance and accountability function as regulatory and institutional mechanisms in the transition toward AI-enabled management accounting. They influence data

ethics, professional competence, algorithmic fairness, strategic decision-making advantages, and ultimately organizational outcomes. X3 can therefore be regarded as a key managerial and institutional lever within the model.

Professional competence and judgment (X4) had a driving power of 4 and a dependence power of 3, a position similar to that of X1. It can consequently be categorized as a relatively influential intermediate variable. Although X4 is itself influenced by governance and infrastructure, once developed it can substantially affect algorithmic fairness, strategic advantages, and organizational outcomes. Substantively, this result is consistent with the role of management accountants because, even in the presence of sophisticated technologies, effective and responsible use of AI remains dependent on human analytical capability, interpretation, professional judgment, and critical assessment. X4 therefore acts as an enabling intermediate factor linking the institutional layer to the outcome layer of the model.

Strategic advantages and decision-making (X5) had a driving power of 2 and a dependence power of 6 and was therefore clearly located within the dependent-variable region. This finding indicates that strategic benefits and improvements in managerial decision-making are primarily outcomes rather than fundamental causes. Such advantages emerge when data ethics, algorithmic fairness, system governance, professional competence, and adequate infrastructure are developed in a coordinated manner. Accordingly, X5 may be interpreted as a dependent strategic outcome reflecting the overall success or failure of the AI-enabled management accounting system.

Infrastructure and implementation challenges (X6) exhibited a driving power of 7 and a dependence power of only 1, making it the strongest driving variable in the entire model. It influences virtually every other dimension but is minimally dependent on them. This position indicates that X6 constitutes the fundamental foundation for the transition to AI-enabled management accounting. Without technical, data-related, system, and implementation readiness, effective governance cannot be established, data ethics cannot be operationalized, professional competencies cannot be effectively utilized, and strategic advantages cannot be realized. X6 should therefore be regarded as the most fundamental driver of the model and a primary point of intervention for organizational policy and implementation planning.

Finally, organizational outcomes and social interactions (X7) had a driving power of 1 and a dependence power of 7, making it the most dependent and final variable in the model. This result indicates that X7 is influenced by virtually all other dimensions while exerting little influence on them. The organizational and social consequences of AI adoption in management accounting therefore represent the final manifestation of the entire system. The quality of these consequences depends on the design of the infrastructure, establishment of governance mechanisms, observance of data ethics, strengthening of professional competence, realization of algorithmic fairness and transparency, and achievement of strategic decision-making advantages. X7 can thus be considered the ultimate outcome variable through which the overall effectiveness of the proposed model becomes observable.

4. Discussion and Conclusion

The present study sought to develop a model for the application of artificial intelligence in the transition to management accounting with emphasis on ethical considerations. The qualitative phase identified 36 key components that were classified into seven principal dimensions: data ethics and privacy, algorithmic fairness and transparency, accountability and system governance, professional competence and judgment, strategic advantages and decision-making, infrastructure and implementation challenges, and organizational outcomes and social interactions. The Interpretive Structural Modeling results subsequently arranged these dimensions into a five-level hierarchy, while MICMAC analysis clarified their relative driving and dependence powers. The overall pattern of

findings indicates that successful transition toward AI-enabled management accounting is not primarily determined by the technological capability of AI itself, but by a broader socio-technical architecture in which infrastructural readiness, governance mechanisms, ethical safeguards, and professional competence jointly shape the strategic and organizational outcomes of AI adoption.

The first major finding was that infrastructure and implementation challenges constituted the strongest driving dimension in the model. This dimension had the highest driving power and the lowest dependence power, indicating that it exerts a foundational influence on almost all other dimensions. This result suggests that before organizations can obtain meaningful benefits from AI in management accounting, they must first establish appropriate technical, data, and organizational foundations. Issues such as system reliability, data integration, compatibility with existing accounting and enterprise systems, implementation costs, and employee resistance therefore represent core prerequisites rather than peripheral implementation concerns. This finding is consistent with the literature emphasizing that AI adoption in accounting depends heavily on the quality of existing information systems, integration capability, data architecture, and organizational readiness [17, 25]. Previous research has similarly shown that business intelligence and enterprise systems create value only when technological resources are effectively assimilated within organizational processes and supported by shared knowledge [7, 9]. The result is also aligned with studies showing that big data and AI applications in accounting face significant barriers when the underlying infrastructure, data quality, and implementation capabilities are insufficient [24, 26]. Accordingly, the strong driving role of infrastructure in the present model confirms that technological readiness is the structural foundation upon which ethical, professional, and strategic AI capabilities are built.

The second major finding concerned accountability and system governance, which emerged as the second strongest driving dimension. Its high driving power and relatively low dependence indicate that governance is a central institutional mechanism through which the effects of AI are regulated and translated into responsible organizational outcomes. The dimension included accountability, shared responsibility, human autonomy, system controllability, and governance and regulation. This result is consistent with the growing recognition that AI-based accounting systems require explicit institutional arrangements to determine who is responsible for system errors, how decisions are monitored, under what conditions human intervention is required, and how ethical and regulatory standards are enforced. Prior studies have highlighted these concerns in accounting information systems and AI ethics, emphasizing the importance of responsibility, control, and professional accountability in technologically mediated decision-making [36, 37]. The finding is also strongly supported by research on the ethical implications of AI in accounting and auditing, which shows that responsibility cannot be transferred entirely to algorithms because developers, managers, users, and professional bodies remain involved in the design, implementation, and interpretation of AI-supported decisions [33, 41]. In a similar vein, corporate responsibility research argues that organizations remain accountable for the social and ethical consequences of algorithmic systems even where decision processes are partially automated [40]. Therefore, the central position of system governance in the model demonstrates that AI adoption in management accounting requires formal mechanisms of oversight, responsibility allocation, controllability, and regulatory compliance.

Data ethics and privacy were identified as an intermediate but influential dimension. Although this dimension was not as foundational as infrastructure or governance, it exerted meaningful influence on algorithmic fairness, strategic outcomes, and organizational consequences. This finding indicates that the legitimacy of AI-enabled management accounting depends heavily on how organizational data are collected, protected, accessed, and reused. The components of data security, privacy, and data misuse reflect concerns that management accounting

systems increasingly rely on integrated financial, operational, employee, customer, and external information. The wider the scope of data use, the greater the potential for privacy violations, unauthorized use, leakage, and secondary exploitation. This result is compatible with previous studies emphasizing the ethical and legal implications of AI-related data processing and the increasing importance of regulatory frameworks governing data use, transparency, and human rights [42, 43]. The ethical implications of AI in accounting have likewise been associated with confidentiality, data responsibility, and potential misuse of sensitive information [33, 34]. Thus, the position of data ethics and privacy as a mediating dimension is conceptually meaningful: infrastructure and governance establish the conditions for data use, while ethical data practices influence whether AI outputs are perceived as legitimate and trustworthy.

Professional competence and judgment also occupied an intermediate position in the structural model. This dimension included users' technical competence, training and retraining, professional judgment, erosion of professional skepticism, and overreliance on AI. The finding suggests that AI does not eliminate the importance of professional expertise; rather, it changes the type of expertise required. Management accountants increasingly need capabilities in data interpretation, system understanding, analytical reasoning, and critical evaluation of algorithmic outputs. This finding is consistent with studies showing that business analytics is transforming the competence profiles of controllers and management accountants by increasing the importance of digital and analytical skills [18, 19]. It also aligns with research indicating that accountants' roles are moving away from routine processing and toward interpretation, strategic advice, and technology-assisted judgment [20-22]. At the same time, the inclusion of reduced professional skepticism and overreliance on AI confirms concerns raised in the literature about excessive automation. Sutton et al. argued that too much automation may weaken human relevance in knowledge-intensive work and reduce active professional engagement [28]. Similarly, AI-related accounting research has noted that automated systems can supplement rather than fully replace human expertise, particularly in contexts requiring contextual interpretation and judgment [29]. The present findings therefore reinforce the view that professional competence functions as an enabling bridge between technological capability and responsible managerial use.

Algorithmic fairness and transparency emerged as a relatively dependent dimension, indicating that it is largely shaped by more fundamental conditions such as infrastructure, governance, data ethics, and professional competence. This dimension included algorithmic transparency, trust in AI, expectation gaps, algorithmic bias, justice and fairness, and distortion of results. The position of this dimension suggests that fairness and transparency are not properties that arise automatically from the use of advanced algorithms; they must be institutionally and professionally produced. This interpretation is strongly aligned with the literature on black-box analytics, which shows that opacity in algorithmic decision-making can undermine users' ability to evaluate the validity and ethical acceptability of outputs [31]. Research on algorithmic explanation similarly stresses the need for users to understand how automated systems generate outcomes and what factors influence their recommendations [32]. In management accounting, such transparency is particularly important because analytical outputs may influence budgeting, performance evaluation, resource allocation, and managerial accountability. Moreover, users' trust in analytics is influenced not only by technical accuracy but also by how credible and interpretable the advice appears [30]. Accordingly, the findings suggest that algorithmic fairness and transparency are downstream outcomes of responsible system design and organizational governance rather than independent technological attributes.

Strategic advantages and decision-making also appeared as a dependent dimension. This result indicates that improvements in analytical accuracy, decision quality, operational efficiency, cost reduction, financial forecasting,

performance measurement, management control, big-data analytics, and fraud detection are consequences of successful implementation rather than starting conditions. This is an important finding because organizations often justify AI adoption primarily in terms of efficiency and decision benefits. The current model indicates, however, that such advantages materialize only when infrastructural, ethical, governance, and professional requirements have already been addressed. This conclusion is supported by previous research showing that AI and analytics can improve accounting estimates, prediction, anomaly detection, and decision quality [11, 12]. Studies of business intelligence and intelligent management accounting systems have also emphasized improvements in forecasting, performance analysis, and managerial decision support [10, 13, 14]. Big data research likewise identifies substantial opportunities for more timely and sophisticated analysis in accounting [5, 15]. Yet the dependent position of this dimension indicates that these benefits are contingent rather than automatic. In other words, AI creates strategic value only when organizations possess the infrastructure, governance, data integrity, and human capabilities necessary to transform algorithmic outputs into defensible managerial decisions.

The final and most dependent dimension was organizational outcomes and social interactions. Its very low driving power and very high dependence indicate that changes in workplace interaction, stakeholder relations, and the role of management accountants represent the cumulative consequences of all other dimensions in the model. This result is theoretically significant because it frames organizational outcomes as the endpoint of the AI adoption process. If infrastructure is inadequate, governance is weak, ethical risks are unmanaged, or professional competence is insufficient, adverse organizational consequences may emerge, including reduced trust, occupational insecurity, social isolation, or conflict among stakeholders. Conversely, where AI is introduced responsibly, it may support the reconfiguration of the management accountant's role toward more analytical and strategic functions. This conclusion is consistent with research showing that digital technologies and AI are transforming the role of accountants and creating new expectations for participation in strategic decision-making [16, 22]. It also corresponds with broader studies emphasizing the relationship between AI, organizational responsibility, and stakeholder interests [35, 40]. Thus, the final outcome dimension reflects the broader social embeddedness of AI adoption and confirms that the success of intelligent management accounting cannot be judged solely by technical performance.

The MICMAC results reinforce the hierarchical ISM findings. Infrastructure and implementation challenges and accountability and system governance were classified as the principal driving dimensions, whereas strategic advantages and decision-making and organizational outcomes and social interactions were strongly dependent dimensions. Data ethics and privacy and professional competence and judgment occupied intermediate positions, suggesting that they function as transmission mechanisms through which foundational conditions affect higher-level outcomes. Algorithmic fairness and transparency also appeared relatively dependent, indicating that ethical legitimacy emerges from the combined functioning of governance, data practices, and professional control. This pattern is consistent with prior work suggesting that AI-based accounting systems should be understood as integrated socio-technical systems rather than as isolated technological solutions [8, 14]. It also corresponds with studies emphasizing that perceived usefulness, user readiness, and implementation context affect the adoption and institutionalization of AI in accounting environments [23]. Overall, the model developed in this study demonstrates that responsible AI-enabled management accounting emerges through a layered process in which infrastructure enables governance, governance and professional capability support ethical and transparent use, and these conditions collectively generate strategic and organizational outcomes.

This study has several limitations that should be considered when interpreting its findings. First, the qualitative phase relied on the systematic analysis of published studies and therefore reflects the scope, terminology, and methodological orientations of the literature available within the selected databases and time period. Second, the structural model was developed on the basis of expert judgment, which is appropriate for ISM but may be influenced by participants' professional backgrounds, experience, and perceptions. Third, although the expert group included both academic and practical specialists, the sample size was necessarily limited because of the specialized nature of the study. Fourth, the model identifies structural relationships and relative driving and dependence powers but does not estimate the magnitude of causal effects among the dimensions. Finally, organizational, regulatory, technological, and cultural conditions may differ across industries and countries, and therefore the precise configuration of the model may not be equally applicable in all contexts.

Future studies can extend the present findings by empirically testing the proposed model using larger samples and quantitative methods such as structural equation modeling, partial least squares structural equation modeling, or longitudinal analysis. Comparative studies across industries, organizational sizes, and national contexts could determine whether the relative importance of the seven dimensions changes under different regulatory, technological, or cultural conditions. Researchers may also examine the individual components within each dimension in greater detail, particularly algorithmic transparency, professional skepticism, data governance, employee resistance, and shared accountability. Longitudinal research would be particularly valuable for examining how the relationships among these dimensions evolve as organizations move from initial AI adoption to routine use and advanced integration. Experimental studies could also assess how different levels of explainability, human oversight, and automation affect management accountants' trust, judgment quality, and reliance on AI-generated recommendations.

Organizations seeking to implement AI in management accounting should begin with infrastructural and governance readiness rather than focusing exclusively on short-term efficiency gains. Priority should be given to reliable data architecture, interoperability with existing accounting and ERP systems, clear access controls, data quality standards, and adequate technical support. Formal governance mechanisms should define responsibility for AI-supported decisions, establish procedures for human intervention, and specify how errors, bias, and ethical concerns are identified and corrected. Management accountants should receive continuous training in AI literacy, data interpretation, algorithmic limitations, and critical evaluation of automated outputs. Organizations should also preserve meaningful human judgment and avoid treating AI-generated recommendations as automatically authoritative. Finally, implementation success should be evaluated not only by cost savings or processing speed but also by transparency, fairness, stakeholder trust, professional accountability, and the broader organizational consequences of AI-enabled decision-making.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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