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The Accounting of Artificial Intelligence Assets: Challenges of Recognition and Measurement of AI as Corporate Assets

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ABSTRACT

The rapid proliferation of artificial intelligence (AI) technologies has created a significant gap between corporate economic reality and financial statement disclosure. While firms invest billions of dollars in AI systems, current accounting standards primarily IAS 38 (Intangible Assets) and IAS 16 (Property, Plant and Equipment) were not designed to accommodate the unique characteristics of AI assets. This paper conducts a systematic literature review of 20 peer-reviewed studies published between 2021 and 2024 to examine the challenges of recognising and measuring AI as a corporate asset. The findings identify five critical challenge domains: (1) recognition criteria ambiguity, (2) measurement model insufficiency, (3) rapid obsolescence, (4) data valuation complexity, and (5) ethical and disclosure deficiencies. We propose a five-tiered AI asset classification framework aligned with existing IFRS principles and provide guidance on recognition, measurement, and impairment testing. The study concludes that standard-setters, including the IASB, must urgently revisit intangible asset standards to reflect the economic substance of AI investments and ensure transparent, comparable financial reporting.

Keywords: *Artificial Intelligence; Asset Recognition; IAS 38; Intangible Assets; Financial Reporting; IFRS*

INTRODUCTION

The twenty-first century has witnessed an unprecedented transformation of healthcare delivery systems through the rapid integration of digital technologies. Electronic health records (EHR), telemedicine platforms, clinical decision support systems, mobile health applications, and digital communication tools have become indispensable components of contemporary clinical practice. While these technologies promise improved patient outcomes, enhanced care coordination, and operational efficiency, their pervasive adoption has simultaneously introduced a new occupational hazard: digital fatigue. This phenomenon, characterized by the physical, cognitive, and emotional exhaustion resulting from prolonged and intensive engagement with digital technologies, has emerged as a pressing concern within healthcare settings globally.

Digital fatigue, sometimes used interchangeably with technostress, technology-induced fatigue, or cyber-fatigue, represents a complex, multidimensional construct that extends beyond simple tiredness. It encompasses a spectrum of adverse experiences including eye strain and visual fatigue, musculoskeletal discomfort, cognitive overload, attentional depletion, emotional exhaustion, and diminished sense of personal accomplishment. In healthcare environments, where technology use is both intensive and high-stakes, the consequences of digital fatigue extend beyond individual worker well-being to affect patient safety, quality of care, and institutional performance.

The magnitude of technology exposure among healthcare professionals has grown substantially over the past decade. Clinicians now spend an average of two hours on EHR documentation for every hour of direct patient care, a ratio that has been described as creating a 'documentation burden' that fundamentally alters the nature of clinical work (Gardner et al., 2018; Kroth et al., 2018). Emergency physicians face additional layers of digital stress through constant connectivity requirements, real-time alert systems, and the need to simultaneously manage multiple digital interfaces during high-acuity situations (Bernburg et al., 2024). Nursing staff are increasingly required to navigate complex digital charting systems, electronic medication administration records, and remote monitoring platforms (Toker et al., 2026; Tolasa & Türkmenoğlu, 2026).

The physical health consequences of digital fatigue in healthcare are well-documented. Prolonged screen time is associated with computer vision syndrome (CVS), characterized by dry eyes, blurred vision, headaches, and neck pain. Musculoskeletal disorders affecting the neck, shoulders, and wrists are prevalent among clinicians who spend extended periods at computer workstations. Sleep disturbances are another significant physical consequence, as blue light emitted by digital screens suppresses melatonin secretion, disrupting circadian rhythms even when screen exposure occurs during daylight hours (Nakshine et al., 2022; Small et al., 2020).

Mental health consequences are equally concerning. The literature consistently demonstrates significant associations between intensive technology use and elevated rates of burnout, anxiety, depression, and reduced psychological resilience among healthcare professionals. Burnout, defined by the World Health Organization as an occupational phenomenon characterized by emotional exhaustion, depersonalization, and reduced sense of personal accomplishment, has reached epidemic proportions in post-pandemic healthcare settings. Meta-analytic evidence indicates that burnout prevalence among EHR-exposed clinicians approximates 40%, representing a substantial attributable risk linked specifically to technology use (Wu et al., 2023).

The concept of technostress, first articulated by Craig Brod in 1984 and subsequently refined by Tarafdar and colleagues, provides a theoretical framework for understanding how technology creates stress through several mechanisms: techno-overload (excessive workload from technology), techno-invasion (technology blurring work-life boundaries), techno-complexity (difficulty mastering complex systems), techno-insecurity (fear of replacement or deskilling), and techno-uncertainty (frequent and disruptive system updates). All five mechanisms have been empirically documented in healthcare contexts (Golz et al., 2021; Bahr et al., 2023).

Despite a growing evidence base, significant gaps remain in the literature. First, most existing studies focus on EHR-related burnout, leaving other digital platforms including telehealth, mobile health applications, and artificial intelligence tools comparatively understudied. Second, the majority of research has been conducted in high-income Western countries, leaving healthcare workers in low- and middle-income settings significantly underrepresented. Third, longitudinal evidence examining how digital fatigue evolves over time, and its relationship to career trajectory and workforce retention, remains limited. Fourth, while interventional frameworks have been proposed, randomized controlled trials evaluating specific digital fatigue mitigation strategies in healthcare contexts are scarce.

The novelty of this review lies in its integrative synthesis of evidence across the full spectrum of digital fatigue manifestations in healthcare, spanning physical, cognitive, and emotional dimensions simultaneously. Unlike prior reviews that have focused narrowly on EHR-related burnout or technostress among specific professional groups, this paper adopts a broad, system-level perspective that encompasses diverse healthcare professional roles, multiple technology platforms, and the interaction between individual vulnerability factors and organizational context. Furthermore, by incorporating the most recent evidence from 2025 and 2026 including emerging research on artificial intelligence-related fatigue and post-pandemic digital transformation effects this review provides the most current and comprehensive synthesis available to date. The findings have direct implications for healthcare administrators, technology designers, policymakers, and occupational health practitioners seeking to address the digital fatigue crisis facing the global healthcare workforce.

Table 1. Summary of AI Asset Classification under IFRS

AI Asset Type	Classification	Applicable Standard	Measurement Approach
Purchased Software (ERP/Analytics)	Intangible Asset	IAS 38	Cost/Revaluation Model
Internally Developed ML Model	Intangible Asset (if criteria met)	IAS 38 + IFRIC 12	Amortised over useful life
Third-party AI-as-a-Service	Operating Expense / ROU Asset	IFRS 16 / IAS 17	Expensed or right-of-use
AI Hardware (GPUs, Servers)	Property, Plant & Equipment	IAS 16	Depreciated straight-line
Data Assets (Proprietary Datasets)	Uncertain – no explicit standard	None specific	Disclosed in notes only
AI Patents / Algorithms	Intangible Asset	IAS 38	Amortised / impairment tested

Source: Authors' synthesis based on IASB standards and reviewed literature (2021–2024)

METHODS

Research Design

This study adopts a systematic literature review (SLR) methodology following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol. The SLR approach is appropriate for synthesising and critically appraising a body of literature on a defined research question, particularly where empirical primary data collection is not the primary objective (Hasan, 2022; Kureljusic & Karger, 2023).

The research proceeded through four phases: (1) identification of relevant literature, (2) screening based on inclusion and exclusion criteria, (3) eligibility assessment through full-text review, and (4) synthesis and thematic coding. The conceptual framework is grounded in the framework of intangible asset theory as codified in IAS 38 and extended by emerging AI governance literature.

Data Sources and Inclusion Criteria

A systematic search was conducted across five academic databases: Scopus, Web of Science, SSRN, Google Scholar, and Consensus.app. The search string combined terms: ("artificial intelligence" OR "machine learning" OR "AI") AND ("accounting" OR "financial reporting" OR "asset recognition" OR "measurement"). The search was limited to peer-reviewed journal articles published between 2021 and 2024, written in English.

Inclusion criteria required studies to: (a) address AI in a corporate or organisational accounting context, (b) engage with at least one dimension of asset recognition, measurement, disclosure, or valuation, and (c) be published in a recognised academic or practitioner journal. Conference papers and grey literature were excluded to maintain quality standards. The final sample comprised 20 studies, which form the reference base for this paper.

Inclusion Criteria and Sample

Thematic analysis was applied to identify recurring challenge domains across the reviewed literature. Each article was coded independently using an inductively derived coding scheme, then synthesised into five overarching themes. The proposed five-tier framework emerged from the convergence of these themes with the existing IFRS conceptual framework, drawing on the asset definition criteria established in IAS 38, IAS 16, and IFRS 16

AI ASSET RECOGNITION & MEASUREMENT DECISION FRAMEWORK

[AI Technology Investment Identified]

↓

Step 1 — Is the AI system identifiable and separable from other assets?

YES → Proceed │ NO → Expense immediately

↓

Step 2 — Does the entity control the AI system (contractual or legal right)?

YES → Proceed │ NO → Disclose in notes only

↓

Step 3 — Does the AI system generate probable future economic benefits?

YES → Proceed │ NO → Expense under IAS 38 development phase

↓

Step 4 — Classify by Tier (see Table 3)

Tier 1–2: Capitalise │ Tier 3: IFRS 16 / Expense │ Tier 4–5: Component/Note

↓

Step 5 — Apply Measurement Model

Cost Model (default) │ Revaluation (if active market exists)

↓

Step 6 — Annual Impairment Test (IAS 36) & Disclosure (IAS 38 para. 118–128)

Figure 1. Conceptual Framework: AI Asset Recognition and Measurement Decision Flow

Source: Authors' elaboration based on IAS 38, IAS 16, IFRS 16, and reviewed literature

Hypotheses Development

Drawing on the three theoretical anchors reviewed above intangible asset theory as codified in IAS 38, institutional theory explaining the legitimacy constraints facing accounting standard-setters, and agency theory addressing the information asymmetry between firms and investors this study advances five interrelated hypotheses. These hypotheses collectively argue that the structural misfit between AI asset characteristics and existing IFRS criteria produces measurable deficiencies across recognition, measurement, disclosure, data valuation, and ethical governance dimensions, ultimately impairing the quality of financial reporting for AI-intensive firms.

H1: The structural characteristics of AI systems particularly their non-separability, data dependence, and ambiguous development phase boundaries cause them to fail the IAS 38 recognition criteria more frequently than comparable intangible assets, resulting in systematic underrecognition of AI value on corporate balance sheets.

IAS 38 requires an intangible asset to be identifiable either separable from the entity or arising from contractual or legal rights. For AI systems, this criterion is inherently problematic. Proprietary machine learning models are rarely separable in the classical sense: their economic value is inseparable from the training datasets, computational infrastructure, and human expertise required to operate and maintain them (Han et al., 2023; Ahmad, 2023). Furthermore, the demarcation between the IAS 38 research phase in which all costs must be expensed and the development phase in which capitalisation becomes permissible is far less deterministic in AI development than in traditional software, where technical feasibility benchmarks are well-established.

Damerji and Salimi (2021) demonstrate that practitioners' perceived usefulness of AI directly shapes their willingness to adopt it in accounting contexts, which implies that management judgment about AI's future economic benefits itself a recognition trigger under IAS 38 is susceptible to systematic cognitive biases. When management lacks AI literacy, AI asset values may be structurally underestimated, leading to off-balance-sheet treatment of economically significant investments (Odonkor et al., 2024).

H2: Neither the cost model nor the revaluation model under IAS 38 provides a reliable measurement basis for AI assets, as cost commingling and the absence of an active AI market introduce material measurement uncertainty, causing inconsistent and non-comparable reported values across AI-intensive firms.

Even when AI systems clear the recognition threshold, the measurement phase presents a distinct set of challenges. The cost model the default measurement basis under IAS 38 requires the reliable identification of directly attributable costs. For internally developed AI systems, however, costs are structurally commingled across hardware acquisition, data labelling, model training cycles, cloud compute, and human expertise, making reliable cost segregation methodologically intractable (Babina et al., 2024; Oldemeyer et al., 2024).

The revaluation model, which would permit AI assets to be carried at fair value under IAS 38.75, is contingent on the existence of an active market. No such market currently exists for proprietary AI models. Černevičienė and Kabašinskas (2024) note that even emerging secondary markets for AI patents and algorithms remain thin, illiquid, and without standardised valuation benchmarks, precluding reliable fair value measurement for the vast majority of AI assets. Hasan (2022) further observes that the rapid pace of AI obsolescence renders conventional amortisation schedules typically anchored to asset life assumptions of five to ten years ill-suited to AI systems that may become commercially obsolete in twelve to twenty-four months.

H3: The absence of mandatory quantitative disclosure standards for AI assets including performance metrics, model obsolescence risk, and governance structures creates a significant information asymmetry between AI-intensive firms and their investors, impairing the decision-relevance of published financial statements.

Institutional theory holds that accounting standards derive their authority from perceived legitimacy within the professional and regulatory community. Where standards fail to mandate disclosure commensurate with the economic significance of an asset class, that legitimacy is eroded and investor decision-making is impaired. Under current IAS 38 paragraphs 118–128, entities are required to disclose narrative descriptions of their intangible assets but are not mandated to provide quantitative information about AI-specific performance metrics, model accuracy, technological risk exposure, or ethical governance structures.

Kureljusic and Karger (2023) demonstrate that AI forecasting models among the most economically significant AI applications in finance function as black boxes that resist external verification, creating a fundamental tension between AI's economic centrality and its accountability opacity. Fedyk et al. (2022) show that while AI demonstrably improves audit quality, the interpretability deficit of AI models limits auditors' capacity to substantiate AI asset values. Peng et al. (2023) extend this concern to the sustainability domain, arguing that opaque AI reporting undermines SDG 17 objectives by impeding financial transparency at the global level.

H4: The exclusion of internally generated proprietary data assets from IFRS balance sheets, driven by their non-separability and cost inestimability under IAS 38, produces a systematic and material understatement of total asset values for AI-intensive firms, widening the observable market-to-book gap.

Agency theory identifies the withholding of value-relevant information as a manifestation of information asymmetry that disadvantages principals (investors) relative to agents (management). The systematic exclusion of proprietary data assets from corporate balance sheets represents perhaps the most economically consequential instance of this dynamic in the digital economy. AI models derive their value almost entirely from the quality and exclusivity of their training data; yet under current IFRS, internally generated data fails the IAS 38 recognition criteria because the cost of data generation is inseparable from operational activities and future economic benefits cannot be reliably quantified (Bahoo et al., 2023; Peng et al., 2023).

Zhao and Gómez Fariñas (2022) argue that this misalignment between economic reality where proprietary datasets of large technology firms command valuations in the hundreds of billions and accounting representation where they appear at zero is structurally unsustainable and represents a material failure of IFRS in the data economy. Kumar et al. (2022) reinforce this by showing that AI-blockchain integration creates composite asset systems whose value is even more difficult to disaggregate, compounding the understatement problem.

H5: The discretionary nature of AI asset capitalisation under current IFRS in the absence of specific recognition criteria, measurement benchmarks, and mandatory governance disclosures creates conditions conducive to opportunistic financial reporting, including earnings smoothing and leverage management, reducing the overall reliability of AI-intensive firms' financial statements.

Agency theory also predicts that when agents possess discretion over asset recognition decisions and that discretion is constrained neither by precise standards nor by verifiable external benchmarks they will exercise it opportunistically in line with their incentive structures. The current recognition and measurement ambiguity surrounding AI assets creates precisely this condition. When firms are permitted to selectively capitalise AI development costs without clear normative boundaries, they gain the ability to smooth earnings trajectories, manage leverage ratios, and present artificially favourable financial positions to capital markets.

Zhang et al. (2023) document this ethical dimension empirically, showing that algorithmic decision-making in managerial accounting raises accountability and bias concerns that have no parallel in traditional accounting ethics frameworks. Lehner et al. (2022) further argue that the normative vacuum surrounding AI-based accounting decisions enables opportunistic behaviour that existing professional standards are ill-equipped to constrain. Ahmad (2023) extends this concern to multinational corporations, demonstrating that AI accounting discretion interacts with cross-jurisdictional regulatory gaps to amplify ethical risk at the global level.

RESULTS AND DISCUSSION

Recognition Challenges

The literature identifies a fundamental and recurring problem: whether AI systems can satisfy IAS 38's recognition criteria at all. Our synthesis shows that internally developed AI projects typically run into the standard's prohibition on capitalizing research-phase expenditures, which requires firms to expense costs incurred before demonstrating technical feasibility. In practice, however, AI development rarely follows the neat, stage-gated progression that IAS 38 implicitly assumes. Model creation involves iterative experimentation, continuous hyperparameter tuning, and frequent pivoting between exploratory research and applied engineering, so determining the precise moment when technical feasibility has been demonstrated is difficult. This fuzziness is compounded by the fact that many AI outputs gain value only after sustained retraining, data accumulation, and integration with operational systems processes that straddle research and development activities and blur the line between capitalizable development work and ongoing R&D or maintenance costs (Han et al., 2023; Hasan, 2022).

The blurred boundary generates important practical and policy consequences. Firms seeking to comply with IAS 38 face significant judgment calls about when to stop expensing and start capitalizing, which can produce inconsistent treatment across entities and undermine comparability; auditors confront equally challenging evidence standards when asked to attest to claims of demonstrated technical feasibility. Moreover, because AI value often materializes through continuous improvement rather than a single deliverable, applying a one-time capitalization decision may misrepresent economic reality capitalizing too early risks recording assets whose future benefits are speculative, while capitalizing too late (or not at all) understates a firm's resource base and competitive position. The result is a systemic tension between a rules-based recognition regime and the iterative, data-driven lifecycle of AI systems, suggesting the need for either refined application guidance within IAS 38 or new standard-setting that explicitly addresses the research-to-deployment continuum characteristic of modern AI development.

Damerji and Salimi (2021) show that practitioners' willingness to adopt AI tools in accounting hinges importantly on their perceived usefulness of those technologies an insight that has direct, if indirect, consequences for asset recognition under IAS 38. Management judgment is central to applying the "probable future economic benefits" test, so if decision-makers view AI primarily as experimental or operational tooling rather than a strategic, capitalizable resource, they are less likely to classify related expenditures as development costs eligible for capitalization. Perceptions of usefulness therefore shape not only implementation choices but also accounting outcomes: firms whose leaders appreciate AI's strategic potential are more likely to invest in governance, documentation, and controls that support capitalization, whereas teams skeptical of AI may treat similar investments as routine expenses.

This behavioral channel creates a systematic recognition bias that can depress reported asset bases across organizations with low AI literacy. When managers lack technical understanding of model lifecycles, data provenance, or the durability of AI-driven competitive advantages, they may underestimate the probability, timing, or magnitude of future economic benefits and consequently refrain from capitalizing qualifying development costs. The result is underrecognition of economically valuable AI resources on the balance sheet, reduced comparability across firms with differing managerial competencies, and persistent information asymmetries for investors and creditors. Addressing this problem requires more than technical accounting guidance: it calls for improved managerial education on AI economics, clearer internal controls and documentation standards that make capitalization judgments auditable, and auditor training so that subjective assessments of "probable" benefits become more consistent and evidence-based.

Measurement Challenges

Even when AI assets qualify for recognition, their measurement presents substantial difficulties. The cost model the default under IAS 38 requires reliable identification of directly attributable costs. For internally developed AI systems, costs are typically commingled across hardware, data acquisition, model training, and human expertise, making reliable cost allocation problematic (Odonkor et al., 2024; Babina et al., 2024).

The revaluation model, which would allow AI assets to be carried at fair value, requires the existence of an active market. No such market currently exists for proprietary AI systems. While secondary markets for AI patents and algorithms are emerging, they remain thin and illiquid, precluding reliable fair value measurement for most AI assets (Černevičienė & Kabašinskas, 2024; Oldemeyer et al., 2024).

Table 2. Key Challenges in AI Asset Accounting

Challenge Area	Core Issue	Practical Problem	Current Practice
Recognition	When does AI meet	Intangible criteria under IAS	Mandatory expense

	the definition of an asset?	38 rarely satisfied by self-developed AI	during development phase
Measurement	Cost vs. fair value of AI models	No active market for most proprietary AI models	Cost model default; inconsistent across firms
Useful Life	Determining amortisation period	AI models become obsolete rapidly; lifespan uncertain	Accelerated amortisation or indefinite life debate
Impairment	Detecting value decline in AI assets	AI performance not directly linked to financial cash flows	Subjective impairment triggers
Disclosure	Transparency of AI asset value and risk	Lack of standardised ESG/AI disclosure frameworks	Qualitative notes only; no quantitative benchmark
Data Valuation	Recognising proprietary datasets as assets	Data lacks separability; generation cost unclear	Off-balance-sheet treatment predominates

Source: Authors' synthesis from systematic literature review (2021–2024)

Data Valuation and Off-Balance-Sheet AI

Perhaps the most underexplored dimension of AI asset accounting is the valuation of proprietary datasets. AI models are only as valuable as the data they are trained on, yet data assets rarely appear on corporate balance sheets. Under current IFRS, internally generated data fails to meet IAS 38 recognition criteria because the cost of generating data is often inseparable from operational activities, and the future economic benefits are highly uncertain (Peng et al., 2023; Bahoo et al., 2023).

This creates a systematic understatement of AI-related asset values. Companies like technology giants that have amassed billions of proprietary data records the fuel for their AI systems — carry these assets at zero on their balance sheets while competitors and analysts ascribe to them valuations in the hundreds of billions. Zhao & Gómez Fariñas (2022) argue that this misalignment between economic and accounting reality is unsustainable and undermines the decision-usefulness of financial statements.

Ethical and Disclosure Dimensions

Zhang et al. (2023), Lehner et al. (2022), and Ahmad (2023) collectively highlight that AI asset accounting is not a purely technical matter it carries significant ethical implications. When firms are permitted to capitalise AI costs selectively, they gain the ability to smooth earnings, manage leverage ratios, and present a more favourable financial position. This flexibility, without clear normative boundaries, creates opportunities for opportunistic reporting.

Current disclosure requirements under IAS 38 paragraphs 118–128 require narrative description of intangible assets but do not mandate quantitative disclosure of AI-specific performance metrics, model accuracy, or technological risk. This qualitative-only disclosure regime limits investors' ability to assess the true value and risk profile of a firm's AI portfolio (Fedyk et al., 2022; Kureljusic & Karger, 2023).

Discussion

The findings of this systematic review confirm that existing IFRS standards are materially insufficient for capturing AI's economic substance. The five challenge domains recognition, measurement, useful life, data valuation, and disclosure are interconnected and mutually reinforcing. Addressing one in isolation will not resolve the overall reporting gap.

The proposed five-tier classification framework (Table 3 below) offers a structured approach to navigating AI asset diversity. Rather than a single universal treatment, the tiered approach acknowledges that acquired AI software, internally developed models, AI-as-a-service subscriptions, hybrid systems, and data assets have fundamentally different economic characteristics that warrant differentiated accounting treatment.

Critically, the framework's recognition criteria align with IAS 38's existing conceptual structure ensuring implementation does not require wholesale standard revision, but rather interpretive guidance and supplementary disclosure requirements. This makes the framework tractable for the IASB without requiring a fundamental reconceptualisation of the intangible asset standard.

The ethical dimensions identified by Zhang et al. (2023) and Lehner et al. (2022) underscore the need for mandatory disclosure of AI governance structures alongside financial measurement. Transparency about AI model limitations, bias risks, and data provenance would significantly enhance the decision-relevance of AI disclosures, particularly for ESG-focused investors (Rana et al., 2021; Kitsios & Kamariotou, 2021).

Table 3. Proposed Five-Tier AI Asset Measurement Framework

AI Asset Tier	Initial Recognition	Impairment Approach	Useful Life / Amortisation
Tier 1 – Acquired AI	Full cost capitalisation	Annual impairment test	Straight-line; 3–7 years
Tier 2 – Internally Developed	Capitalise post-feasibility costs only	Performance benchmarking	Accelerated; 2–5 years
Tier 3 – AI-as-a-Service	Expense or IFRS 16 ROU	Usage-based review	Not applicable
Tier 4 – Hybrid AI Systems	Component approach (IAS 16 + IAS 38)	Segment impairment	Component-by-component
Tier 5 – Data & Algorithm	Disclose in notes; no capitalisation yet	Annual review of economic utility	No amortisation standard

Source: Authors' proposed framework based on IAS 38, IAS 16, IFRS 16 and reviewed literature.

CONCLUSIONS

This paper demonstrates that the accounting treatment of artificial intelligence assets represents one of the most complex and consequential challenges facing the accounting profession in the digital era. Through systematic review of 20 peer-reviewed studies, five critical challenge domains have been identified: recognition ambiguity, measurement insufficiency, rapid obsolescence, data valuation complexity, and ethical disclosure deficiencies.

The proposed five-tier AI asset framework provides a practical, IFRS-compatible structure for recognition and measurement that standard-setters and practitioners can adopt without wholesale revision of existing standards. The framework's primary contribution lies in disaggregating the heterogeneous category of 'AI assets' into economically meaningful tiers, each with appropriate recognition criteria, measurement models, and disclosure requirements.

The broader implication is that the IASB must treat AI accounting reform as a priority. As AI becomes the primary driver of corporate value creation, the persistence of off-balance-sheet AI values will increasingly erode the decision-relevance of IFRS financial statements and undermine the trust that underpins global capital markets..

REFERENCES

Ahmad, A. (2023). Ethical implications of artificial intelligence in accounting: A framework for responsible AI adoption in multinational corporations in Jordan. International Journal of Data and Network Science. https://doi.org/10.5267/j.ijdns.2023.9.014

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics. https://doi.org/10.1016/j.jfineco.2023.103745

Bahoo, S., Cucculelli, M., & Qamar, D. (2023). Artificial intelligence and corporate innovation: A review and research agenda. Technological Forecasting and Social Change. https://doi.org/10.1016/j.techfore.2022.122264

Černevičienė, J., & Kabašinskas, A. (2024). Explainable artificial intelligence (XAI) in finance: A systematic literature review. Artificial Intelligence Review, 57. https://doi.org/10.1007/s10462-024-10854-8

Chen, B., Wu, Z., & Zhao, R. (2023). From fiction to fact: The growing role of generative AI in business and finance. Journal of Chinese Economic and Business Studies, 21, 471–496. https://doi.org/10.1080/14765284.2023.2245279

Damerji, H., & Salimi, A. (2021). Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting. Accounting Education, 30, 107–130. https://doi.org/10.1080/09639284.2021.1872035

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2021). Artificial intelligence and business value: A literature review. Information Systems Frontiers, 24, 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process? Review of Accounting Studies, 27, 938–985. https://doi.org/10.1007/s11142-022-09697-x

Han, H., Shiwakoti, R., Jarvis, R., Mordi, C., & Botchie, D. (2023). Accounting and auditing with blockchain technology and artificial intelligence: A literature review. International Journal of Accounting Information Systems, 48, 100598. https://doi.org/10.1016/j.accinf.2022.100598

Hasan, A. (2022). Artificial intelligence (AI) in accounting & auditing: A literature review. Open Journal of Business and Management. https://doi.org/10.4236/ojbm.2022.101026

Kitsios, F., & Kamariotou, M. (2021). Artificial intelligence and business strategy towards digital transformation: A research agenda. Sustainability. https://doi.org/10.3390/su13042025

Kumar, S., Lim, W. M., Sivarajah, U., & Kaur, J. (2022). Artificial intelligence and blockchain integration in business: Trends from a bibliometric-content analysis. Information Systems Frontiers, 25, 871–896. https://doi.org/10.1007/s10796-022-10279-0

Kureljusic, M., & Karger, E. (2023). Forecasting in financial accounting with artificial intelligence: A systematic literature review and future research agenda. Journal of Applied Accounting Research. https://doi.org/10.1108/jaar-06-2022-0146

Lehner, O., Ittonen, K., Silvola, H., Ström, E., & Wührleitner, A. (2022). Artificial intelligence based decision-making in accounting and auditing: Ethical challenges and normative thinking. Accounting, Auditing & Accountability Journal. https://doi.org/10.1108/aaaj-09-2020-4934

Odonkor, B., Kaggwa, S., Uwaoma, P. U., Hassan, A. O., & Farayola, O. A. (2024). The impact of AI on accounting practices: A review. World Journal of Advanced Research and Reviews. https://doi.org/10.30574/wjarr.2024.21.1.2721

Oldemeyer, L., Jede, A., & Teuteberg, F. (2024). Investigation of artificial intelligence in SMEs: A systematic review of the state of the art and the main implementation challenges. Management Review Quarterly, 75, 1185–1227. https://doi.org/10.1007/s11301-024-00405-4

Peng, Y., Ahmad, S. F., Ahmad, A., Shaikh, M. A., Daoud, M., & Alhamdi, F. (2023). Riding the waves of artificial intelligence in advancing accounting and its implications for sustainable

development goals. Sustainability. https://doi.org/10.3390/su151914165
Rana, N., Chatterjee, S., Dwivedi, Y., & Akter, S. (2021). Understanding dark side of artificial intelligence (AI) integrated business analytics: Assessing firm's operational inefficiency and competitiveness. European Journal of Information Systems, 31, 364–387. https://doi.org/10.1080/0960085x.2021.1955628
Zhang, C., Zhu, W.-D., Dai, J., Wu, Y., & Chen, X. (2023). Ethical impact of artificial intelligence in managerial accounting. International Journal of Accounting Information Systems, 49, 100619. https://doi.org/10.1016/j.accinf.2023.100619
Zhao, J., & Gómez Fariñas, B. (2022). Artificial intelligence and sustainable decisions. European Business Organization Law Review, 24, 1–39. https://doi.org/10.1007/s40804-022-00262-2