مجلة الشروق للعلوم التجارية
الترقيم الدولي ISSN: 1687/8523
ترقيم دولي الكتروني Online :2682-356X
رقم الايداع بدار الكتب المصرية 2007/12870
البريد الالكتروني sjcs@sha.edu.eg
موقع المجلة : https://sjcs.sha.edu.eg/index.php

SH. A.
إكاديمية الشروق
عضو اتحاد الجامعات العربية

المعهد العالي للحاسبات وتكنولوجيا المعلومات

AI-generated Information: What is the Financial Reporting Framework?

Shehata Elsayed Shehata
Professor, Department of Accounting and Auditing, Faculty of Commerce, Alexandria University
Dean of High Institute for Computer & Information Systems- Abi Qir
shehata2001eg@yahoo.com

Safaa Mohammed El Halawany
Assistant Lecturer, Information Systems department
High Institute for Computer & Information Systems- Abi Qir
safyelhalawany@gmail.com

Keywords:

AI, Information, financial statements, intangible assets, disclosure

التوثيق المقترح وفقا لنظام APA :

Shehata, Shehata Elsayed, El Halawany, Safaa Mohamed (2024), AI-generated Information: What is the Financial Reporting Framework?, Al-Shorouk Journal of Commercial Sciences, special volume, The Higher institute for Computers and Information Technology, Al-Shorouk Academy, page 483 - 500

"AI-generated Information: What is the Financial Reporting Framework?"

Shehata Elsayed Shehata
Professor, Department of Accounting and Auditing, Faculty of Commerce, Alexandria University
Dean of High Institute for Computer & Information Systems- Abi Qir
shehata2001eg@yahoo.com

Safaa Mohammed El Halawany
Assistant Lecturer, Information Systems department
High Institute for Computer & Information Systems- Abi Qir
safyelhalawany@gmail.com

Abstract

In recent decades, the pervasive integration of Artificial Intelligence (AI) technologies has revolutionized the business landscape, playing a pivotal role in the generation of valuable information. This working paper explores the expanding influence of AI in businesses and the implications for financial reporting, specifically focusing on the recognition, measurement and disclosure of AI-generated information as intangible assets. As organizations increasingly rely on AI to enhance operational efficiency, optimize decision-making processes, and gain a competitive edge, the need to accurately reflect the value of AI-driven outputs in financial statements becomes paramount. AI-generated information disclosure provides stakeholders, regulators, and investors with a comprehensive understanding of the economic, ethical, and strategic implications of AI assets, as they navigate the dynamic landscape shaped by the increasing influence of AI technologies. By examining current practices and regulatory frameworks, this paper aims to provide insights into establishing standardized accounting for AI-generated information as intangible assets and ensuring transparency in financial reporting.

Keywords—AI, Information, financial statements, intangible assets, disclosure.

I. Introduction-

Accounting information represents the main input to decision-making models for users and stakeholders who rely on it to make rational decisions. Studies in the field of financial accounting seek to reduce the degree of information asymmetry, which is necessarily reflected in reducing conflicts of interest and agency problems. Therefore, financial statements are useful to the extent that the information they contain is reliable, representative of reality, and capable of providing users with the predictive ability this information contains to make the right decisions (Cuc, 2021; Bubeck, 2023; Habbal, et. Al., 2024; Nyholm, 2024).

As a result of technological development and the digital economic environment for business models, the importance of obtaining high-quality data and information generated by artificial intelligence that is useful in the decision-making process and achieving a competitive advantage has increased (Cockcroft, et. Al., 2018; Sihombing, 2023). Organizations gather and generate vast quantities of diverse data forms from various sources, commonly referred to as "Big Data," as part of their routine business activities. They leverage this data through the analysis of sophisticated algorithms and high computing power to extract valuable information, facilitating improved decision-making processes (Toth, 2021)

Big Data refers to large data volumes that require advanced storage and retrieval facilities. It includes both structured and unstructured data, such as texts with changing lengths and lacking context. This ingenious integration of algorithms, Big Data, and processing capacity is commonly referred to as "machine learning” or, more broadly, as "Artificial Intelligence" (AI) (Ding et al., 2020).

Machine learning Algorithms enable companies to transform raw data into AI- generated information and reap economic benefits. The value of the intangible resource "data" has grown significantly as a result of the growing digitization of business models brought about by technologies, but it's possible that the existing financial reporting framework is not relevant to accurately reflect this significant driver's value of AI- generated information. (Pei and Vasarhelyi, 2020). Large volumes of diverse data, referred to as "Big Data," are generated and collected by organizations then analyzing data with sophisticated algorithms in order to obtain information that would help them make better decisions (Faroukhi, et al., 2020). Machine learning techniques can be extremely beneficial in refining accounting estimations, which in turn improves the value of financial information for investors (Ding, et al., 2020).

Objective- Utilizing "self-learning" algorithms and robust computing capabilities, businesses are converting Big Data into AI-generated information, reaping economic advantages, and have rapidly emerged as crucial strategic resources in the global economy. Despite their significance, their value is not formally acknowledged in financial statements, resulting in an increasing gap between book and market values and limiting the decision usefulness of the underlying financial statements.

This working paper explores the expanding influence of AI in businesses and the implications for financial reporting, specifically focusing on the recognition, measurement and disclosure of AI-generated information as intangible assets depending on an analysis of related accounting statements and literature review of academic studies.

II. Analysis of Literature reviews-

A. Machine learning and data transformation

Artificial intelligence (AI) refers to computer systems capable of performing complex tasks that historically only a human could do, such as reasoning, making decisions, or solving problems (Nyholm, 2024). Leading researchers (Bubeck, 2023; Ahmad, et. Al., 2024; Habbal, 2024) define artificial intelligence as “the study and design of intelligent systems that understand their environment and take actions that increase their chances of success,” while John McCarthy - who coined this term in 1955 - defines it as “the science and engineering of making intelligent machines.”

Machine Learning (ML) is a subtype of AI, combines the practical "learning" of human intelligence with the ability to learn and improve analysis using algorithms (Ahmad, A. Y. B., et. Al., 2024). Deep Learning technology is its most prominent manifestation, and it is based on the development of artificial neural networks that mimic in the way they operate the human brain, meaning that they are able to experiment, learn, and develop themselves independently without human intervention using Cloud Technology (Helm, et al., 2020; Vărzaru, 2022).

The conversion of Big Data into economic gain necessitates a combination of various resources (for example, human resources; technical experience, innovative mindset, computing equipment, self-learning, and sophisticated, deep-state algorithms), in a continuous dynamic cycle. Artificial intelligence-driven procedures transform raw Big Data into valuable business information, providing a competitive advantage (Faroukhi et al., 2020). The initial procedure involves generating Big Data. As discussed earlier, Big Data can be generated from a range of internal sources and devices. Additionally, it can originate from external providers, either available for free (such as publicly accessible data) or through purchase. To effectively utilize the generated data, the next crucial procedures involve selecting and transforming the data (Mehrvand, 2024).

Hence, the second procedure commences with the collection of pertinent data tailored to the specific purpose. This process involves selecting and amalgamating suitable sources, assessing data quality, and performing aggregation and cleaning procedures. (Helm, et. al., 2020)

In the third procedure, the preselected, cleaned, and aggregated data undergo analysis using AI technology, characterized by sophisticated algorithms and high computing speed. This analysis aims to identify patterns and trends that may be significant for managerial purposes or external use by customers and partners, resulting in the extraction of intelligent information (Pei, D. and Vasarhelyi, 2020; Sihombing, 2023)

The transformation of Big Data into AI-generated information necessitates economic resources, including IT infrastructure such as a database management system (DBMS) (de Villiers, 2024); data analytics tools like KNIME, Tableau, and Power-BI; AI technology; and, critically, personnel with the expertise to pose relevant questions and apply appropriate algorithms to convert Big Data into actionable information.

Continuously generated additional data carry the potential for new information, necessitating regular revisitation of the entire process. The previous procedures are thus interconnected, demonstrating a continual inflow of feedback. This iterative nature may result in algorithm refinement, as seen in deep-state neuronal networks (NN) (Ding et al., 2020; Mehrvand, 2024). These networks learn from each new piece of information to enhance decision-making and predictions. A tangible illustration could be cloud-based accounting applications with a neural network core (Nyholm, 2024; Habbal, 2024)

With each customer interaction and new case, such as a new invoice, the volume of data and potential information extraction grows. The neural network (NN) core learns from these additional examples. Over time, the software's prediction and interpretation of cases become highly accurate, significantly enhancing the software's value for both customers and the company. The NN core accumulates experience from each case, contributing to its improved performance. In certain instances, value creation stems not only from the data itself but also from the synergy with algorithms like NN. Recognizing and acknowledging this combined contribution becomes essential. This perspective is supported by both technical and cognitive viewpoints, with scholarly literature affirming that the scope of Big Data surpasses human cognition (Duan et al., 2019; Losbichler and Lehner, 2021), necessitating processing and evaluation by sophisticated machine learning.

There are two avenues for leveraging the data: internal and external usage. Internal usage involves gaining a competitive advantage by utilizing the data, such as obtaining deeper insights into business processes to support complex, data-driven decision-making (Aboagye, et al., 2021). This internal utilization enhances competitiveness and economic benefits, contributing to cost reduction, error minimization (e.g., setting optimal prices), and better understanding of customer needs (Park, 2020).

On the other hand, external usage implies that the data can be either sold or made available to external partners (Faroukhi et al., 2020). From this external perspective, both raw Big Data and AI-information generate economic benefits through revenues and cash flows derived from sales or leasing arrangements (Monteiro, 2020).

In certain instances, the same dataset can generate revenue through both internal and external usage. An innovative and recent illustration of this concept is the "digital twins" A digital twin (DT) can be conceptualized as a virtual model representing physical objects, processes, and/or entire systems. The creation of this virtual model necessitates substantial computing power, sensors continuously generating data (sometimes through "edge devices"), sophisticated algorithms, and physics-based computing frameworks (Cuc, 2021; Golovina et al., 2020; Miehe et al., 2021).

The digital twin (DT) can be viewed as AI-generated information that enables vendors and customers to simulate and customize physical objects in the virtual world. This capability allows companies to significantly reduce process and production costs. For instance, vendors can showcase complex products in virtual showrooms, facilitating easy and cost-effective customization, ultimately leading to a more personalized production mode. Simultaneously, data generated by customers can be collected on the vendor's platform to further enhance the digital twin (Cuc, 2021; Miehe, 2021). Learning from the obtained data improves not only the simulation but also the development of future physical products, contributing to the optimization of maintenance schedules.

B. Recognize AI- generated information value in financial statements.

AI- generated information and Big Data have become critical strategic resources globally. However, their worth is not acknowledged in financial statements. The increasing gap between book and market values limits the usefulness of financial statements for decision-making (Toth, 2021; Xiong, 2022). In order to narrow the gap between book value and market value, first we need to redefine "economic resource" term, it refers to has the potential to produce economic benefits. Data may generate economic benefits after reaching a specific level when combined with other data sources, at which point it becomes Big Data and may have been sufficiently analyzed by advanced algorithms to provide AI-generated insights (Barker, 2018; Birch, 2021; Ahmad, A., Abusaimeh, 2024). Due to the current practices and regulatory frameworks, data might fit the criteria of an economic resource. However, "potential" is an undefined legal term giving possibility for interpretation and ambiguity (Beerbaum, 2019; Sihombing, 2023; de Villiers, 2024).

Financial reporting incurs costs, and it is essential that the benefits derived from financial reporting justify these expenses. Evaluating whether the benefits of providing information outweigh the associated costs is frequently a matter of judgment. This is due to the challenge of identifying and quantifying all the costs and benefits associated with the information included in General Purpose Financial Reports (GPFRs). (CF par. 3.35 – 3.36).[1]

According to The Conceptual Framework for General Purpose Financial Reporting by Public Sector Entities, Dec 2023; an asset is "a resource presently controlled by the entity as a result of a past event." (CF par. 5.6). The term control implies the current ability to guide the use of the economic resource and collect the economic rewards that may result from it. A resource is "a right to either service potential or the capability to generate economic benefits or a right to both." (CF par. 5.6A).

To gain economic advantage, the organization needs to take safeguards to assure the durability of its control, such as data protection and security measures. Indeed, leaked data would become publicly visible (loss of control) and may no longer provide an economic benefit. AI-generated information or Big Data alone may be identified. Nevertheless, the lack of reliable measurement of its

[1] General Purpose Financial Reports (GPFR) DEC 2023; Cost benefit par. 3.35 – 3.36

benefits and value estimation would certainly impair recognition and assessment of the asset (KPMG, 2020).

As data does not meet the criteria of a monetary asset and lacks physical substance, it falls under the definition of an intangible asset (IAS 38 par. 8). Moreover, the definition of intangible assets stipulates that the intangible asset must be identifiable and controlled by the entity (IAS 38 par. 11). Identifiability is determined by the notion that the intangible asset is either separable, meaning it can be separated from the entity and sold, transferred, licensed, or exchanged, or arises from contractual or other legal rights (IAS 38 par. 12). Identifiability enables the separation of intangible assets from goodwill (IAS 38 par. 11).

Control of intangible assets implies that "the entity has the power to obtain the future economic benefits" (IAS 38 par.13) and "to restrict access to others to those benefits" (IAS 38 par. 13). Generally, data is likely to fulfill both criteria: identifiability and control. Blockchain technology can be employed to ensure actual ownership and prevent others from accessing the data (Huang, et. Al., 2020; Wang, 2022).

C. Measurement of AI- generated information value

Obtaining control over AI-generated information has varying economic benefits. There are two avenues for measuring AI-generated information either self-acquired/processed or externally acquired. When evaluating AI-generated information for self-acquired, the initial valuation should consider all costs associated with data development, collecting, and analysis. Data conversion costs include labor for data collection, refining, analysis, production overheads for transforming raw Big Data into AI-generated information and subsequently be adjusted based on fair value or net present value. Reliable cost accounting is crucial for accurately identifying, categorizing, allocating, and reporting data conversion costs. For externally acquired AI- generated information, the initial valuation should reflect the historical purchase cost and then be updated to fair value. However, if the fair value of the asset can be determined based on an active market at a subsequent assessment date, the revaluation model is implemented from that point onward (IAS 36). This necessitates evaluating the data at fair value during subsequent assessments, with any increase or decrease recognized through other comprehensive income. Nevertheless, it is rare for an active market to exist for an intangible asset. Additionally, even if AI-generated information is sold, they typically represent unique assets, and according to IAS 38, the price paid may not sufficiently indicate the fair value of another asset. Hence, while IAS 38 allows for the possibility, the requirement of an active market (as defined by IFRS 13) may render it challenging to assess data at fair value. However, this situation may evolve with the emergence of several data market platforms, which could eventually lead to the development of an active market for data assets (Pei, D. and Vasarhelyi, 2020; Xiong, 2022; de Villiers, 2024).

According to the inherent characteristics of AI- generated information as intangible asset, challenging to be identified, variability (value subject to change with time, market circumstances, and usage conditions), exchangeability (capable of benefiting both parties). It's crucial to emphasize that data is more valuable for current decision-making when it is recent (Xiong, 2022). In 2016, “Gartner”, a leading information research and consultancy firm, released the world's first data asset evaluation model. Gartner, in collaboration with clients, valuation experts, accountants and economists introduced the following six formal information valuation models—each with a different purpose. Some are financial measures (cost value of information “CVI”, market value of information “MVI”, and economic value of information “EVI”) while others are foundational metrics (intrinsic value of information “IVI”, business value of information “BVI”, and performance value of information “PVI”). The model considers factors such as relevance, quantity, quality, scarcity, transaction nature, industry nature, scope and expected benefits.

Yanlin, (2020) suggests that machine learning algorithms can be employed to assess the value of data assets. Artificial neural networks possess significant self-organizing, adaptive, and self-learning capabilities, enabling objective evaluation and prediction of the intrinsic value of data itself. This approach not only mitigates the impact of subjective factors and fuzzy randomness inherent in human evaluation but also ensures the objectivity and accuracy of assessment outcomes. Additionally, it offers strong dynamics, furnishing a crucial basis for determining data prices.

Previous literature has primarily focused on two crucial aspects of AI- generated information evaluation: process costs (collection and application) and data asset characteristics (such as data type and complexity. We advocate for employing deep learning algorithms based on AI- generated information characteristics to formulate intangible asset valuation model centered on four dimensions: data type, validity period, data application scope, and complexity. The algorithm generates outputs including the internal and market values of the AI- generated information. Deep learning-generated accounting estimates potentially surpass human estimates due to their consistent and systematic utilization of archival (training) data, a capability often lacking in humans.

D. Disclosure and presentation of AI- generated information value

Accounting estimates constitute a critical component of financial statements, as many disclosures within companies' financial statements necessitate estimation. They pervade financial statements, significantly impacting a company's financial position and operational outcomes. As organizations increasingly rely on AI to enhance operational efficiency, optimize decision-making processes, and gain a competitive edge, the need to accurately reflect the value of AI- generated information in financial statements becomes dominant. AI-generated information disclosure provides stakeholders, regulators, and investors with a comprehensive understanding (Ding, et al., 2020).

This doesn't inherently mandate that internally AI- generated information must be acknowledged as intangible assets on the balance sheet, as achieving this may currently pose challenges, as discussed earlier. However, the balance sheet constitutes just one aspect of reporting, and there are alternative avenues, such as enhancing disclosures in the notes or even introducing a separate statement, to evaluate the value of an economic resource (Sætra, 2021; Toth et al., 2021). This aligns with current sustainability reporting requirements, which mandate entities to provide sustainability-related information alongside general purpose financial reporting (IFRS Foundation, 2022).

III. Conclusion and future research opportunities

A. Conclusion

The escalating prominence of Artificial Intelligence (AI) in businesses has ushered in a transformative era, wherein AI technologies play a pivotal role in the generation of invaluable information. This working paper has shed light on the imperative task of recognizing and disclosing AI-generated information as intangible assets within the realm of financial reporting. As organizations increasingly leverage AI to gain a competitive advantage, optimize processes, and unlock new opportunities, accounting standards such as International Financial Reporting Standards (IFRS) and Generally Accepted Accounting Principles (GAAP) must adapt to effectively capture the value of these intangible assets (Habbal, et. Al., 2024; Nyholm, 2024).

The convergence of technological advancements and financial reporting practices introduces a myriad of challenges, ranging from the determination of fair value to the establishment of standardized methodologies for disclosure. However, recognizing AI-generated information as a distinct category of intangible assets is vital for ensuring accurate and transparent financial reporting. IFRS standards need to evolve to provide comprehensive guidelines that align with the unique characteristics and complexities of AI-generated assets (Cuc, 2021; Bubeck, 2023).

As this paper has explored, the recognition, measurement and disclosure of AI-generated information present opportunities for standard-setters to foster consistency and comparability across industries. Striking a balance between providing useful information to stakeholders and maintaining the relevance and reliability of financial statements is paramount. The collaboration between accounting professionals, regulators, and the technology sector is essential to develop a framework that not only captures the economic value of AI-generated assets but also ensures that financial reporting remains a reliable tool for decision-makers (Cockcroft, et. Al., 2018; Sihombing, 2023).

In navigating this dynamic landscape, businesses and standard setters alike must remain vigilant to emerging trends, technological advancements, and evolving industry practices. The recognition of AI-generated information as intangible assets in financial reporting is not merely a compliance exercise; it is an essential step towards accurately reflecting the true value and impact of AI on an organization's financial health. As we move forward, continued research, dialogue, and collaboration will be crucial in shaping accounting standards that facilitate a transparent and informative representation of the increasing role of AI in businesses.

B. Future Research suggestions-

- The impact of AI- generated information recognition in financial statements on stock prices.
- The relationship between AI- generative reports and firm’s financial performance.
- Impact of AI- generated information disclosure on firm’s value.
- The relationship between AI- generated information and audit quality.
- The interrelation between sustainability reports and artificial intelligence.
- The effect of AI- generated information on audit planning.
- The effect of AI- generated information on auditor professional judgements.

References:

- Aboagye-Otchere, F., Agyenim-Boateng, C. and Enusah, A. (2021), “A review of big data research in accounting”, ***Intelligent Systems in Accounting, Finance and Management,*** Vol. 28 No. 4, pp. 268-283.
- Ahmad, A. Y. B., Tiwari, A., Nayeem, M. A., Biswal, B. K., Satapathy, D. P., Kulshreshtha, K., & Bordoloi, D. (2024). Artificial Intelligence Perspective Framework of the Smart Finance and Accounting Management Model**.** ***International Journal of Intelligent Systems and Applications in Engineering***, *12*(4s), 586-594.
- Ahmad, A., Abusaimeh, H., Rababah, A., Alqsass, M., Al-Olima, N., & Hamdan, M. (2024). Assessment of effects in advances of accounting technologies on quality financial reports in Jordanian public sector. ***Uncertain Supply Chain Management***, *12*(1), 133-142.
- Barker, R. and Teixeira, A. (2018), “Gaps in the IFRS conceptual framework”, ***Accounting in Europe***, Vol. 15 No. 2, pp. 153-166.
- Beerbaum, D., Piechocki, M. and Puaschunder, J.M. (2019), “Measuring accounting reporting complexity with customized extensions XBRL–A behavioral economics approach”, ***Journal of Applied Research in the Digital Economy (JADE),*** Vol. 1 No. 3, pp. 4-42.
- Birch, K., Cochrane, D.T. and Ward, C. (2021), “Data as asset? The measurement, governance, and valuation of digital personal data by Big Tech”, ***Big Data and Society***, Vol. 8 No. 1, 20539517211017308.
- Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., Horvitz, E., Kamar, E., ... & Zhang, Y. (2023). **Sparks of artificial general intelligence: Early experiments with gpt-4.** *arXiv preprint arXiv:2303.12712*.
- Cockcroft, S., & Russell, M. (2018). Big data opportunities for accounting and finance practice and research. ***Australian Accounting Review***, *28*(3), 323-333.

- Cuc, M. (2021), “Improving the decision-making process by modeling digital twins in a Big Data environment”, ***Management and Marketing Journal***, Vol. 19 No. 1, pp. 138-154
- de Villiers, C., Dimes, R., & Molinari, M. (2024). How will AI text generation and processing impact sustainability reporting? Critical analysis, a conceptual framework and avenues for future research. ***Sustainability Accounting, Management and Policy Journal***, *15*(1), 96-118.
- Ding, K., Lev, B., Peng, X., Sun, T., & Vasarhelyi, M. A. (2020). Machine learning improves accounting estimates: Evidence from insurance payments. ***Review of accounting studies,*** *25*, 1098-1134.
- Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019), “Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda”, ***International Journal of Information Management***, Vol. 48, pp. 63 - 71.
- Faroukhi, A.Z., El Alaoui, I., Gahi, Y. and Amine, A. (2020), “Big data monetization throughout big data value chain: a comprehensive review”, ***Journal of Big Data,*** Vol. 7 No. 1, pp. 1-22.
- Golovina, T., Polyanin, A., Adamenko, A., Khegay, E. and Schepinin, V. (2020), “Digital twins as a new paradigm of an industrial Enterprise***”, International Journal of Technology***, Vol. 11 No. 6, pp. 1115-1124.
- Habbal, A., Ali, M. K., & Abuzaraida, M. A. (2024). Artificial Intelligence Trust, Risk and Security Management (AI TRiSM): Frameworks, applications, challenges and future research directions. ***Expert Systems with Applications***, *240*, 122442.
- Helm, J. M., Swiergosz, A. M., Haeberle, H. S., Karnuta, J. M., Schaffer, J. L., Krebs, V. E., ... & Ramkumar, P. N. (2020). Machine learning and artificial intelligence: definitions, applications, and future directions. Current reviews in musculoskeletal medicine, 13, 69-76.
- Huang, S., Wang, G., Yan, Y. and Fang, X. (2020), “Blockchain-based data management for digital twin of product”, ***Journal of Manufacturing Systems***, Vol. 54, pp. 361-371.

- IFRS Foundation (2021), "Proposed targeted amendments to the IFRS foundation constitution to accommodate an international sustainability standards board to set IFRS sustainability standards".
- IFRS Foundation (2022), "Exposure draft on IFRS S1 general requirements for disclosure of sustainability-related financial information".
- IFRS Foundation (2023), "**IAS 38 Intangible Assets**".
- IFRS Interpretations Committee (2021), "Configuration or customization costs in a cloud computing arrangement (IAS 38 intangible assets): agenda decisions", available at: https://www.ifrs.org/projects/completed-projects/2021/configuration-or-customisation-costs-in-a-cloud-computing-arrangement-ias-38/#about
- International Public Sector Accounting Standards Board (IPSASB), (2023), **Conceptual Framework for General Purpose Financial Reporting**.
- KPMG (2020), **Insights into IFRS: KPMG's Practical Guide to International Financial Reporting Standards**, 17th ed., 2020/2021, Mytholmroyd.
- Losbichler, H. and Lehner, O.M. (2021), "Limits of artificial intelligence in controlling and the ways forward: a call for future accounting research", ***Journal of Applied Accounting Research,*** Vol. 22 No. 2, pp. 365-382.
- Mehrvand, S., Boucher, M. A., Kornelsen, K., & Amani, A. (2024). Comparing three machine learning algorithms with existing methods for natural streamflow estimation. ***Hydrological Sciences Journal***, *69*(1), 79-94.
- Miehe, R., Waltersmann, L., Sauer, A. and Bauernhansl, T. (2021), "Sustainable production and the role of digital twins–Basic reflections and perspectives", ***Journal of Advanced Manufacturing and Processing***, Vol. 3 No. 2, p. e10078.
- Monteiro, D., Monteiro, L., Ferraz, F. and Meira, S. (2020), "Big data monetization: discoveries from a systematic literature review", ***Out,*** Vol. 9, pp. 54-60.

- Nyholm, S. (2024). Artificial Intelligence and Human Enhancement: Can AI Technologies Make Us More (Artificially) Intelligent?. ***Cambridge Quarterly of Healthcare Ethics,*** *33*(1), 76-88.
- Park, K.T., Lee, J., Kim, H.-J. and Do Noh, S. (2020), "Digital twin-based cyber physical production system architectural framework for personalized production", ***The International Journal of Advanced Manufacturing Technology,*** Vol. 106 No. 5, pp. 1787-1810.
- Pei, D. and Vasarhelyi, M.A. (2020), "Big data and algorithmic trading against periodic and tangible asset reporting: the need for U-XBRL", ***International Journal of Accounting Information Systems***, Vol. 37, 100453.
- Sætra, H.S. (2021), "A framework for evaluating and disclosing the ESG related impacts of AI with the SDGs", ***Sustainability***, Vol. 13 No. 15, p. 8503.
- Sihombing, R. P., Narsa, I. M., & Harymawan, I. (2023). Big data analytics and auditor judgment: an experimental study. ***Accounting Research Journal***, 36(2/3), 201-216.
- Toth, A., Suta, A. and Szauter, F. (2021), "Interrelation between the climate-related sustainability and the financial reporting disclosures of the European automotive industry", ***Clean Technologies and Environmental Policy,*** Vol. 24, pp. 437-445.
- Vărzaru, A. A. (2022). Assessing the Impact of AI Solutions' Ethical Issues on Performance in Managerial Accounting. ***Electronics,*** *11*(14), 2221.
- Wang, S., Zhang, Y., & Guo, Y. (2022). A blockchain-empowered arbitrable multimedia data auditing scheme in IoT cloud computing. Mathematics, 10(6), 1005.
- Xiong, F., Xie, M., Zhao, L., Li, C. and Fan, X. (2022), "Recognition and evaluation of data as intangible assets", ***SAGE Open***, Vol. 12 No. 2, 21582440221094600
- Yanlin, W., & Haijun, Z. (2020, May). Data Asset Value Assessment Literature Review and Prospect. **In *Journal of Physics: Conference Series*** (Vol. 1550, No. 3, p. 032133). IOP Publishing.