Artificial Inteligence's (Ai) Adoption in Accounting: Managing Large Language Models (Llms)

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ABSTRACT

Introduction: This paper examines the use of artificial intelligence applications to support accounting decisions and it tries to answer the following question: can artificial intelligence assist accounting professionals and what role it has compared to human expertise?

Literature review/research gap: This research contributes to the extant literature in a threefold way. First, it expands the debates on how accountants can leverage AI and are influenced by it. Second, it identifies the main trust issues that have so far blocked their extensive adoption. Third, it argues that, in order to advance theories in this area, the accounting field needs empirical studies that allow policymakers and managers to make informed decisions concerning organizational challenges and necessary adaptations.

Research method: This study considers the tool of Large Language Models (LLMs), that allow companies to automate tasks and make better decisions given their natural language processing capabilities (Rowdur, 2023), and is informed by recent advances in artificial intelligence-based publications, including quantum information research.

Findings: this paper presents how AI technology has influenced the accounting profession so far and in what ways this discipline could be affected in the future, to understand the impact of knowledge-based systems on human users' knowledge acquisition and retention and considering that, as the development of LLMs continues and despite their impressive abilities, organizations face trust issues when adopting these tools.

Theoretical and practical implications: the present study can inform both the theory and the practice and considering that in the near future professional hybrids will emerge, the area of AI in accounting will certainly benefit from interdisciplinary research (Hasan, 2021). Thus, accounting and information science scholars have to collaborate with data scientists to find theoretical frameworks and choose the consequent adequate algorithmic solutions (Kemper and Kolkman, 2019), including information-theoretical concerns with regard to the data needed and how to guarantee a widespread diffusion of AI.

Keywords: Large language models, artificial intelligence, accounting, trust, ethics.

INTRODUCTION

AI is an emerging technology that imitates human judgment and cognitive skills and anticipates competitive advantages to those adopting it (Munoko et al., 2020).

Accounting firms are increasingly using AI in their auditing and advisory functions, in order to save time, have a faster data analysis, enhanced client service, more accuracy, more in-depth insight into business processes, and these plan to continue its use in areas such as audit planning risk assessments, tests of transactions, analytics, and the preparation of audit work-papers (Munoko et al., 2020).

AI can be considered as an 'umbrella' term that includes sophisticated machine learning algorithms that learn from Big data and predict the future (Lehner et al., 2022).

Instead, big data refers to a setting in which data sets have reached a vast volume, so that complexity has to be managed, stored and retrieved in an adequate amount of time (Xie, 2022).

Thus, Big Data can be defined as extremely large sets of unstructured data, gathered so fast, from different sources and in various forms that it is way beyond the processing power of a traditional server (Xie, 2022).

According to a 2001 report, Gartner expressed that Big Data is defined by three V's (namely 'volume', 'velocity', and 'variety'); in 2012 'veracity' was included, that represents the outcome of data analysis and the requirements about data trust; similarly, in 2012 IDC defined the 4th V as 'value', highlighting that Big Data applications need to increase firms' value (Zakir et al., 2015).

Data Analytics is the mean to extract value from these huge volumes of information and it enables the processing of unstructured information (Zakir et al., 2015); instead, data mining is the application of certain algorithms for extracting patterns from data, allowing the discovery of hidden knowledge in them (Amani and Fadlalla, 2017).

This can enhance managers' capabilities in discerning patterns in data that would otherwise take years to discover using other approaches, to estimate the likelihood of an event, and to control both accuracy of the data and legitimacy of its requests (Amani and Fadlalla, 2017).

It is obvious that accountants can benefit from big data, having a supporting role in the exploratory analysis of structured and unstructured data (Richins et al., 2017).

In particular, for public accounting firms' big data can provide assurance over the sheer amount of unstructured data, along with new consulting opportunities, considering that these firms face potential increased competition from those more advanced in data analysis (Richins et al., 2017).

Also, advances in AI are changing how digital accounting in the future will collect and process data, considering cognitive multi-functional capabilities and that of decision-making in complex scenarios (Lehner et al., 2019).

This term 'digital accounting' summarizes a variety of interdisciplinary research streams (as it considers both digital information technology and accounting) belonging to the automatization and digitalisation of accounting processes through emerging technologies, dealing for example with digital technology's role in reporting and accounting, the detection of fraud (Amani and Fadlalla, 2017) and the new competencies required for accounting professionals (Lehner et al., 2019).

As depicted in Figure 1, data analytics can be conceptualized along two measures: data type and analysis approach (Richins et al., 2017).

Data can be structured or unstructured: unstructured data are those lacking organizational rigor (usually generated from sources such as YouTube, and it may be in diverse forms such as video, text, audio) and constitute the largest portion of extant data.

Instead, structured data is highly organized, typically deriving from the firm's transactions.

The dimension of analysis can be either problem driven or exploratory.

Through a problem-driven approach (theory driven hypotheses testing), problems are identified, potential causes are formalized into hypotheses, and those concerns are transformed into solutions: in a post big data world, a problem-driven analysis is possible only on unstructured data (Richins et al., 2017).

In contrast, exploratory analysis is independent of formal hypothesis testing; it needs the attention of management accountants that have to summarize large data sets to understand the key characteristics (Richins et al., 2017).

Accountants' have the professional skill set to filter out the redundant data and include relevant content in exploratory analysis, to then interpret the results within a business framework (Richins et al., 2017).

DEVELOPMENT OF RESEARCH PROPOSITIONS

Given the initial question of this paper (Can artificial intelligence assist accounting professionals and what role it has compared to human expertise?), to elaborate on research issues in accounting information systems it can be noted that different methodologies and corresponding research questions can be addressed at different stages of a technology (O'Leary, 2009).

In this sense, O'Leary (2009) focused on the maturity curve, the adoption curve, and some of the Gartner's

		Data	
		Structured	Unstructured
Analysis Approach	Problem Driven Analysis	Problem driven analysis on structured data (pre big data)	Problem driven analysis on unstructured data (post big data)
	Exploratory Analysis	Exploratory analysis on structured data (post big data)	Exploratory analysis on unstructured data (post big data)

Figure 1: Matrix of Data and Analysis Appoach in a Pre and Post Big Data World. Source: (Richins et al., 2017)

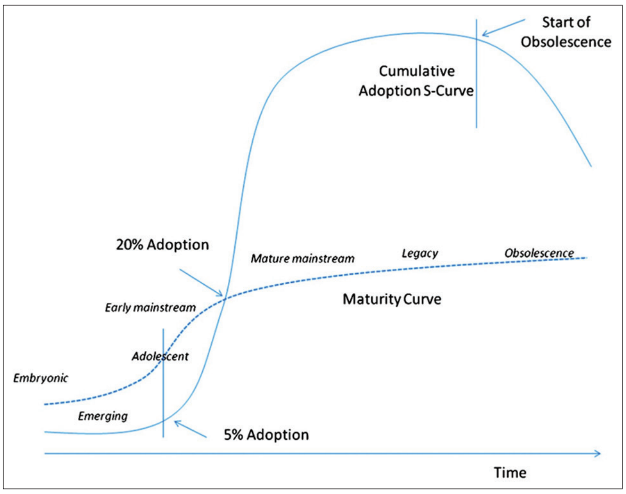

Figure 2: Adoption and Maturity Curve's levels and adoption rates

tools to analyse both of these stages of a technology; here the maturity curve (also called "S" curve) is used to trace a technology's change over time as it matures to accommodate user needs.

In Figure 2 is provided an illustration of these curves integrated with seven qualitative levels of the framework (namely embryonic, emerging, adolescence, early mainstream, mature mainstream, legacy, obsolescence), considering that different portions of the maturity curve and the adoption curve have different characteristics and different research opportunities (O'Leary, 2009). Additionally, the maturity curve can be expanded by considering more capabilities, as in Figure 3.

In particular, the emerging level is when technologies are "emerging" out of the laboratories to be placed in application environments for the first time, vendors start commercialization, and there are deployments by industry leaders, just like it is happening with AI.

However, since the technology and its underlying models have not stabilized, academics may contribute to the overall development of the technology, for example by providing models that facilitate organizational adoption with further developments in the technology, and researchers can investigate what is going right with applications and what is going wrong (O'Leary, 2009).

At this stage, vendors may interact with academics to help technology diffusion, and researchers might develop prototypes or pilot implementations (O'Leary, 2009).

As technologies move from embryonic to emerging and even into later stages and are placed into organizational settings, issues other than the functionality (for example security) of the technology become important (O'Leary, 2009).

When there is more comprehension of the technology, research investigating the consequences of the new technology might be initiated, and data can be gathered from organizational settings.

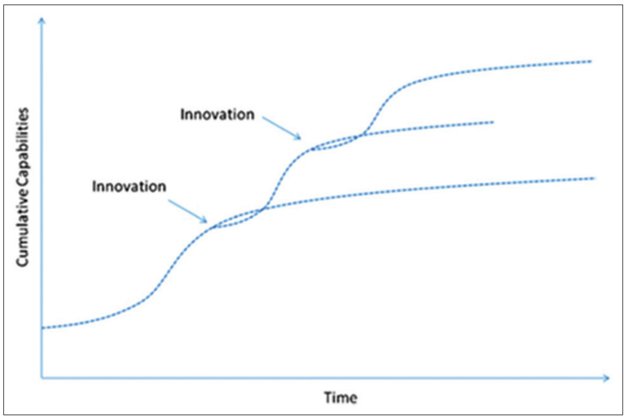

Figure 3: Maturity curve with innovations. Source: O'Leary (2009)

However, the sample of data tends to be biased since the technology is of the first generation and it often must be customized to meet user needs, the number of adopters is small, the technology has a high price (O'Leary, 2009).

At this point, behavioural research may be used to find limitations or strengths in technology use, for example by helping understand a technology's limitations from the user's perspective and drive evolution to the second generation; expert opinion may be of interest in the case of emerging issues, such as the situation of the technology in organizations (O'Leary, 2009).

As an example, technology at the emerging stage is first-generation and is more costly than it will be at later stages (O'Leary, 2009).

However, as the technology moves into later maturity levels, other research approaches become preferred, allowing researchers to gather larger samples of technology uses and to examine issues such as the impact on accounting measures, without biased samples, using empirical archival studies; at these stages, design science, case studies, surveys, and opinions are not of general interest (O'Leary, 2009).

Another method that serves as a starting point for practitioners and researchers to estimate or predict the duration of competitive advantage for an emerging technology such as AI is that of Stratopoulos and Wang (2022).

Their method provides a structure that may help researchers and practitioners better approach this daunting task, even though estimation or prediction often requires enormous judgement, and no single method can cover all the complexities in the technology adoption environment.

This is particularly useful as AI gives a platform for accountants to explore the latest technology driven aspects, and that AI can perform the following accounting tasks (Gusai, 2019):

- It helps companies in obtaining, consolidating, and merging data from different sources: this saves time and helps them to plan goals effectively.
- AI facilitates digital files' search and access: this increases the precision of the auditing done as a firm's financial transactions can be looked upon easily.
- It can review receipts, expenses and identify if there is any breach of accounting policies and procedures.
- It helps resolve queries of the consumers and keep track of their account balance, pending bills etc.

- AI interprets the role of accountants as to check the financial position of a company and helps to make decisions in a clear-cut way, after accountants have applied their technical knowledge about financial and non-financial transactions. For example, organizing a database in a cost-effective manner and producing new techniques for analysis saves time so that focus can be shifted from manual accounting tasks to other aspects, such as decision making, building relationships and problem management.

Additionally, LLMs can support accountants' work in textual tasks, such as drafting memos for clients, even those of a technical nature (for example, discussing the difference between financial reporting and taxation methods of depreciation); summarizing regulatory requirements for given topics; synthesizing and comparing large bodies of text, like comparing financial reporting standards; conducting analytical procedures on comparative financial statements: preparing footnotes to financial statements based on numeric and textual input data; brainstorming risks as part of Enterprise Risk Management or fraud assessment tasks; in understanding an entity and its industry environment (Street and Wilck, 2023).

With regard to the potential for displacement of accounting job tasks due to AI applications, it is important to analyse the task content of the accounting work as well as to understand when and to what extent these tasks will be substituted by smart systems (Stancheva-Todorova, 2018):

- The most time consuming and susceptible to automation part of the accounting job is represented by bookkeeping.

The logic behind the double entry system enables the specific coding of accounting entries.

The ledger records complex business transactions after these are disaggregated and translated in accounting terms.

Machine learning technologies can fully automate this process, so that the accuracy of accounting data and the timing of recording will be improved.

- AI applications can prevent and detect fraud, as machines cannot be corrupted by money or power as they act in accordance with predetermined rules.

Instead, human decisions and actions could damage companies, such as in case of asset theft, tax avoidance, financial statement falsification.

- AI could also be beneficial in revenue forecasting.

In times of uncertainty, information asymmetry and inherent risks, it is difficult to find models and techniques that provide accurate forecasting.

The use of predictive models, based on machine learning algorithms, can improve the quality of the forecast data and consequently the processes of budgeting and strategic management.

Anyway, accountants must avoid the risk of inherent biases by paying attention to the quality of the data set being used for forecasting and planning.

- Another area with great potential for automation is represented by financial accounting and reporting.

A challenge is the increasing number of regulations that need to be transformed into if-then rules and decision trees suitable for AI algorithms.

- Analysis of large amounts of unstructured data comprising emails, contracts, graphs, etc. can be improved by application of deep learning models.

ISSUES WITH LLMS AND CORRESPONDING SOLUTIONS

Forensic accountants have to be cautious when working with LLM (as trust in LLMs remains elusive) and they provide principles and recommendations to guide accounting professionals. This since, as of February 2023 (Street and Wilck, 2023):

- LLMs do not have specialized knowledge in the accounting domain, for example lacking the ability to distinguish between variances or key indicators in financial text. Because its training data is not specialized for the field of accounting, it may not detect which accounting method is to be used when there are several alternatives or distinguish between acquiring a given financial instrument as an asset or issuing a financial instrument as a liability or equity.

An exception to this observation is FinBERT, a cutting-edge LLM tailored for financial texts introduced by Huang et al. (2023). The authors compared its performance with that of other machine learning algorithms to find that FinBERT (that is based on Google's BERT algorithm) is significantly more accurate than other approaches that are used in accounting research, including random forest and the LM dictionary.

Huang et al. (2023) also documented that FinBERT's advantage over other algorithms is especially large when the training sample is small (likely because FinBERT considers contextual information in financial text) and they further demonstrate FinBERT's superior performance in sentiment classification (finding evidence that FinBERT better captures earnings conference calls' textual sentiments, which corroborates the main results) and that it has a capacity to process ESG-related discussions.

This study of Huang et al. (2023) has implications for academic researchers and expands the growing literature examining textual analysis in financial economics by introducing FinBERT and demonstrating its superior performance over algorithms developed in accounting research, as it remained unclear whether and how much these LLMs outperform simpler algorithms when conducting accounting tasks even though these tend to excel at NLP tasks using general texts.

- LLMs is unable to discuss current events or incorporate recent changes (for example in accounting, auditing, or tax standards) into its models, as its knowledge is limited to a given period.
- LLMs' responses may be inaccurate even though users tend to be biased by believing that their responses are correct, due to LLMs' skill at conversational language.

This "fluency heuristic" shows that, the easier a concept is to process, the more likely a person is to evaluate it as correct (Hertwig et al., 2008).

- LLMs may rely on assumptions that are not provided in a prompt.
- LLMs do not always provide explanations on their method or their rationale for answering. Research is underway to help improve the visibility and interpretability of neural networks, models, and algorithms used in AI, like LLMs. Additionally, because of the "black box" nature of the machine learning models powering LLMs, LLMs' response to the same task may differ between different users or may change for a given user at different points in time.
- The knowledge of LLMs is limited to the data available during training, often lacking crucial information regarding a company's operations.
- LLMs may occasionally provide incorrect or misleading information, even though their responses resemble those of humans. This is particularly problematic in sectors where precision and safety are paramount, such as finance.
- LLMs cannot provide appropriate responses when it's difficult to comprehend a given situation's specific context and nuance. This can provoke significant miscommunication in companies with complex operations and numerous stakeholders.
- LLMs can perpetuate existing biases in their training data, resulting in outputs that cause ethical problems. These biases can lead to public relations issues, legal & regulatory challenges, and a deterioration of employee and customer trust.
- Because its knowledge is based on a stratification of training data over time, ChatGPT does not adequately distinguish current and active information from outdated or replaced information. This is particularly problematic because accounting standards, regulations, and tax law change over time.
- Additionally, by deriving from training material, it may be unable to recognize copyrighted text, plagiarizing another work.
- ChatGPT does not provide a confidence level for its responses to assist users in identifying which responses are most likely to contain errors. For example, in its current version (GPT-3.5) the references provided may not refer to articles which actually exist.

Anyway, LLMs can be effectively applied in the accounting domain, and accounting and financial professionals can strategically leverage these technologies by considering the following suggestions (Street and Wilck, 2023):

- LLMs are better at preliminary tasks than higher skill tasks. However, LLMs may be effectively used by dividing large tasks into smaller subtasks that lead to the completion of the whole job. For example, task the LLM with calculating only a single portion of the balance sheet rather than an entire balance sheet.
- LLMs can be a useful resource to help draft language, but their outputs must be sceptically reviewed and corrected based on accountants' expertise and ensuring that it is aligned with the accountants' objectives in the prompt. For example, accountants should adopt a sceptical mindset and critically assess the responses provided by LLMs as required of auditors in AS 1015, paragraph 07.
- Accountants can explore and leverage the abilities of LLMs in retrieving, synthesizing, interpreting, comparing, and drafting textual content, but they should not rely upon LLMs for quantitative tasks. For example, LLMs may have trouble doing calculations.
- Artificial intelligence can learn from human users with reinforcement learning as they continue to be developed, and subject matter experts can provide valuable feedback to avoid the same errors.
- Leverage LLMs' general knowledge across a variety of domains to complement human tasks, as an ability-enhancer.

THE HUMAN-IN-THE-LOOP APPROACH

At this point it is clear that LLMs can execute routines and mundane tasks quickly, but it is critical to have human skills and judgment to verify LLM's outputs and make final decisions.

Thus, the best way to manage an AI tool like an LLM is to have a 'human-in-the-loop' approach to ensure the accuracy and dependability of AI-generated insights, and incorporating human work into AI decision-making can offer the following advantages (Rowdur, 2023):

- Human experts have to ensure the accuracy of AI-generated responses to avoid costly errors. This validation procedure ensures organisations can rely on LLMs without compromising safety or quality.
- LLMs need human expertise to select outputs that are appropriate to the context and to generate more relevant and accurate responses.

This to ensure that AI-generated insights align with an organisation's needs and objectives and that LLMs become a more valuable asset for decision-making.

- Continuous improvement: As human experts review and correct AI-generated outputs, the LLMs can learn from these modifications, resulting in ongoing performance enhancements.

This iterative process assists businesses in maximising the value of their AI investments over time.

- Human validation can incrementally establish trust among stakeholders if LLM-generated insights are accurate. This confidence is indispensable for the widespread adoption of AI technologies and for realising their full potential.
- Companies can address potential biases in AI-generated outputs by incorporating human experts in the review process. This ensures that decisions are ethical and fair and reduces the possibility of reputational harm or legal repercussions.

From a practical standpoint, organisations that are trying to implement a successful human-in-the-loop strategy could observe the following suggestions (Rowdur, 2023):

- Determine which tasks and decisions are most crucial to the success of your organisation and require the highest level of precision; then, integrate LLMs into these areas while maintaining human oversight.
- Develop a clear and systematic procedure for human experts to review and validate AI-generated outputs. Creating a dedicated team or integrating AI validation into existing workflows may be required.
- Ensure that employees involved in the validation process have the capabilities and tools to review and correct outputs generated by AI effectively, that are well-trained and aware of the benefits and flaws of LLMs.
- Regularly assess the performance of the LLMs and the efficacy of the human validation procedure to check if it meets your organisation's needs.
- Achieve more seamless integration of LLMs by encouraging open communication and sharing insights and improvements between human experts and AI developers.
- Share stories of AI-driven successes to show how LLMs enhanced decision-making, efficiency, and creativity.

ETHICAL IMPLICATIONS OF AI

At this point it's important to discuss the ethical impact of AI on managerial accounting, as its actors and the complexity of their interactions cause ethical dilemmas, and this complexity could be aggravated by smart, AI-based technologies (Lehner et al., 2022).

This since, compared with other areas in accounting, the application of AI in management accounting has a deeper impact and is more likely to provoke ethical challenges.

In fact, firstly, nowadays management accounting has the main function to support activities throughout the firm, which involves a variety of stakeholders.

Hence, issues may arise due to conflicting ethical positions when applying AI.

Second, the use of AI may be exacerbated by the subjectivity and difficulty of managerial accounting and decision-making processes.

In particular, Zhang et al. (2023) investigate the unique ethical impacts on managerial accountants and on other three types of stakeholders, namely regulators, developers and managers in charge of AI adoption. In particular, two aspects are worth discussing (Zhang et al., 2023):

- First, modern management accounting has the main role of supporting activities of the entire business, involving a variety of stakeholders: when adopting and using AI, concerns and challenges may arise due to conflicting ethical positions.
- Second, the use of AI may be exacerbated by the complexity and subjectivity of decision-making and managerial accounting processes.

For example, there are still no accounting standards that regulate how to generate managerial accounting reports using AI, as it only has to conform to the decision-making procedure of each individual organization.

In particular, a potential ethical risk that managerial accountants have to face is isolation due to the use of AI, with other long-term impacts of AI on employees and organizations being power over user, accessibility of AI, accountability of stakeholders when adopting AI.

Anyway, this risk of isolation due to AI is mitigated by the elimination of face-to-face meetings or phone communications among personnel and provides an online platform in which managerial accountants can identify abnormal indicators, explain reasons behind them and insert the motivations into the platform, so that are useful to make decisions (Zhang et al., 2023).

Another concern regarding AI is that reliance on mathematical techniques could reduce expert knowledge, and this may result in significant de-skilling effects on the workforce and cause a "de-professionalizing" effect in work environments that are highly technically oriented.

More broadly, ethical risks may impact on managerial accountants' actions, considering transparency and trust of AI, gaps between user expectations of AI and actual use, bias, result distortion, and user competence.

As managerial accountants have more experience and training, some ethical concerns may be reduced, such as user competency and expectation gaps.

Other concerns to mention are bias, result distortion, and AI transparency and trust.

Lehner et al. (2022) examine five challenges related to AI-based ethical decision-making in accounting, namely: privacy and related data protection problems; (in) transparency; accountability; trustworthiness; objectivity; and consequent bias problems.

Therefore, managerial accountants' use of AI could increase ethical risks and should be managed to mitigate bias, unfairness, damage to user autonomy and independence, and inappropriate decisions.

The adoption and use of AI in managerial accounting also requires accountability among stakeholders, that should eliminate or reduce ethical risks, as well as unethical behaviours due to incompetence of the actor.

In particular, managerial accountants should have the necessary skills to prevent ethical risks before/during AI usage, they should follow (ethical) rules of conduct, create adequate policies for AI's implementation and use, and establish monitoring mechanisms and codes of conduct.

They should also be accountable for adequately planning and arranging the entire process of purchasing and implementing AI systems and should coordinate and manage all stakeholders.

Then, it's important that managerial accountants communicate with regulators, system developers, managers, and this throughout the entire system and process, that is from the initial analysis to the phases of implementation and use, as well as during maintenance and update.

For example, managerial accountants should communicate with system analysts to identify any ethical risks when using AI and should provide timely feedback to managers regarding ethical impacts when using AI, such as result distortion or its effects on users' autonomy.

Other scholars that forecast the ethical implications of the use of AI in auditing, given its inherent features, nature, and intended functions, are Munoko et al. (2020) that provide a conceptual analysis using past studies as well their inferences based on the reported use of the technology by auditing firms; they also analyse policy and governance responsibility for this emerging technology.

Similarly, Smallman (2022) argues that it's important to consider the wider social effects of advanced technologies, like AI, on institutions and societies by rethinking the governance and evaluation mechanisms.

To do this, this author proposes a Multi-Scale Ethics (MSE) approach (Figure 4) that is a guide to consider the impact of their technologies (over time) on the scale of the individual, groups and communities, the institution, the nation, globally, and the framework also considers any interactions between the scales that might be generated by AI, without being a hierarchy while moving up the scale.

To enable a rich understanding of the concerns raised by these technologies, and therefore a much greater change of anticipating and addressing them, Smallman's framework accepts AI and digital technologies as socio-technical systems, which produce technologies and social arrangements: AI is seen as a driver of structural change rather than just a tool (Smallman, 2022).

Smallman (2022) notes that the guidelines for general AI revolve around four 'core' concerns, namely transparency, fairness, responsibility, privacy, with other significant issues being those related to bias, technical robustness, and public trust.

Kemper and Kolkman (2019) stress the importance of transparency, emphasizing the role of a critical audience and unbiased engagement, in which absence transparency measures are at risk of being empty signifiers.

These authors separate the value of transparency from the practical way in which transparency takes shape and consider that the measures toward algorithmic accountability are most effective if we consider them an assemblage of people and machines, in which the value of transparency depends on engaging critical and informed audiences.

Using the idea of scale (as a way to order and analyse the effects of technologies as well as to organise complexity within living organisms) and drawing on extant literature, the Multiscale Ethics Framework (Figure 1) acknowledges that risks and benefits are not distributed evenly and introduces a topography of impacts into ethical evaluations of technologies (Smallman, 2022).

This structure helps to explore the issues at different scales, considering the wider sociological effects of their technologies alongside 'traditional' ethical concerns affecting the individual.

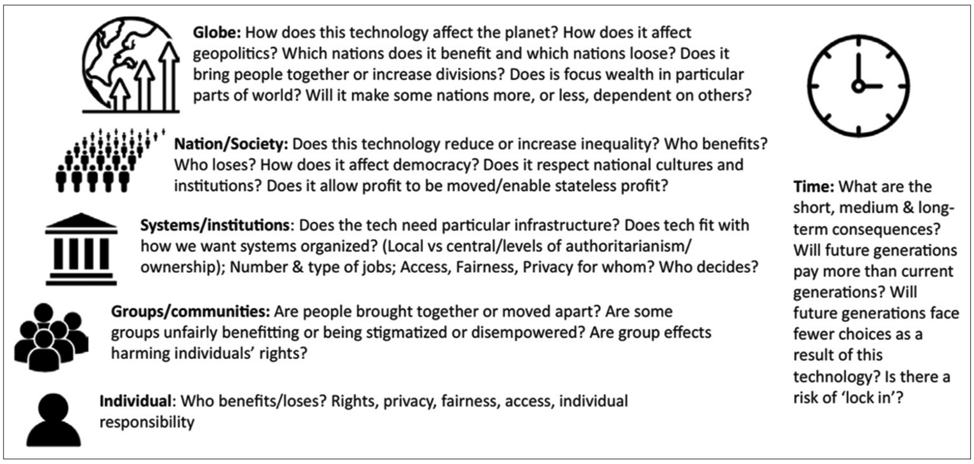

Figure 4: The Multiscale Ethics Framework. Source: Smallman (2022)

QUANTUM CONCEPTUAL APPLICATIONS TO ACCOUNTING INFORMATION

In this section we will outline a few applications of quantum information to the accounting system, from an information content school perspective that combines the information science and economics perspective by viewing accounting as a managed information channel, distanced from its double-entry structure (Demski et al., 2006).

Obviously, accounting as a social science has its own salient features that may have no counterparts in a quantum mechanical setting; likewise, there may be no parallels of quantum features in a social setting (Demski et al., 2006).

Anyway, the modelling of the accounting and the struggles with measurement are similar to those experienced in quantum information theory; thus, solutions in one field may shed light in the other: for example, accountants may learn from entanglement how to cope with irresolvable uncertainty (Demski et al., 2006).

This requires a discussion on probability assessment, endogenous expectations, endogeneity, error-correction mechanisms, the accounting environment.

Probability Assessment

A key aspect to the behaviour modelling in the information content approach is probability assessment, that is also important in accounting areas such as depreciation and uncollectible of accounts receivables.

In order to rethink this concept, we can consider the nature of probability in quantum information theory and its use of ''probability amplitude'', that includes the possibility of mixing between different conditions, such as physical and logical probability (Demski et al., 2006).

Probability assessment in accounting is subjective, affected by transaction designs, and limited by human cognition; experimental human subjects, just like qubits, do not follow the laws of logical probability (Demski et al., 2006).

The information content school explicitly (while the measurement school implicitly) focuses on what can be learned about an entity's prospects or a manager's behaviour by observing the output of information sources, especially that of the accounting system (Demski et al., 2006).

The central feature is partial resolution of uncertainty (just like it happens with quantum information), and the entity and its manager are affected by accounting measurements (Demski et al., 2006).

Endogenous Expectations

The current state of accounting research can be described as excessively taking an exogenous view of how raw data are produced, while including endogenizing expectations may help to create a broader and more integrated view of accounting (Demski et al., 2006).

When examining the impact of accounting information on the market, the managers' opportunistic behaviour in the accrual process should be considered; additionally, the standard setters should consider how the reporting units react to their actual and potential behaviour (Demski et al., 2006).

Another consideration is that accounting estimates reflect the managers' expectations, which presumably stem from managers' actual and anticipated transactions, transactions that may well be affected by the accounting itself (Demski et al., 2006).

This concept of 'endogenous expectations' in accounting has a parallel in quantum mechanics: accordingly, when combining probability amplitudes of different alternatives, the result may affect the interference between the probability amplitudes, which further affect the probability of an event (Demski et al., 2006).

Additionally, the usefulness of accounting measures cannot be the same for valuation (that is the entity's theorized equilibrium path) and evaluation (that is the distinction between behaviours on and off the equilibrium path), and if synergy implies quantum-like interference, then the control problem of an entity has to be addressed in terms of aggregated performance measures (Demski et al., 2006).

Endogeneity Issues in Accounting Information

The design of double-entry information displays what and when measurements are to be recorded and requires the consideration of the aspects of recognition and aggregation; for example, to pay attention to sales data that are aggregated for reporting purposes (Demski et al., 2006).

Inter-temporal aggregation is another important design consideration, that is the time at which a sale is recorded: for example, a new product innovation is recorded only after sales are complete, regardless of estimated profitability (Demski et al., 2006).

Indeed, special techniques, such as qualifying special purpose entities, can accelerate recognition of gains in the double-entry recording, but various design questions arise regarding the level of detail to preserve and when it's best to take measurements (Demski et al., 2006).

Moreover, extant regulations call for specific disclosures on information that are often outside the formal double entry system (Demski et al., 2006).

Similarly, to design of double-entry information, also the quantum experiment is based on careful design of the device and measurements that are to be recorded, even though physicists are more free of regulatory constraint and appear to struggle with information extraction issues, that is the essence of quantum information (Demski et al., 2006).

For example, auditors are key endogenous actors in the reporting process, but the measurement school does not consider their importance (Demski et al., 2006).

The problem with these design issues, including the distinction between formal double entry inclusion and mere disclosure, is that the ''measurement school'' in accounting does not provide the precise meaning of the terms ''relevant'' and ''reliable'', that are notions of the measures produced by the double-entry system (Demski et al., 2006).

This leaves accounting researchers and practitioners with little guidance on how to measure or understand accounting information, let alone connect to the underlying resource allocation issues as in a value of information analysis, requiring the consideration of both the double entry structure and the economic forces (Demski et al., 2006).

Now, while the functioning of classical markets, in an economic sense, could provide the conceptual foundations, the problem is that when the notion of perfect and complete market collapses, not only ''perfect measurement'' is impossible, but it's difficult to measure the underlying economic values (Demski et al., 2006).

The aggregation and recognition questions and the economic trade-offs are clarified by the information content approach, in terms of both the users of the double-entry system and the consequences of one vs. another.

This happens through a social science perspective, where the focus is on humans, while the measurement school takes more of a physical approach; the role played by endogeneity differs, in particular whether the design choices and attendant behaviours include self-directed choice (Demski et al., 2006).

In this way, economic forces are central to the analysis, and we avoid the imprecise guidance of relevance, reliability and even perfect markets of the measurement school and the connected double-entry framework: just as entropy in classical information science, also relevance and reliability (that are qualitative characteristics regarding the value of information) cannot substitute the underlying economic forces (Demski et al., 2006).

Error-Correction Mechanisms

Accounting systems have unavoidable measurement errors, but some are actually intentional; auditors play a role to minimize the errors while producing accounting information, including application of the required measurement methods (Demski et al., 2006).

Thus, in the accounting system, the nature of human interaction adds another level of uncertainty, and only the information content school treats as central aspects those of the measurement's effects and of the actors' roles (Demski et al., 2006).

To improve audit judgment and how auditors interact with clients it is possible to do a comparison with quantum information: in fact, the response of managers to the auditors tends to be less neutral compared to a correction code that restores the quantum mechanical state of a particle in the case of error-correcting schemes (Demski et al., 2006).

The equivalent phenomenon of quantum systems is known as decoherence, which leads to information loss and errors.

In fact, after a particle or entity is prepared in a particular quantum state, it may lose this state as a result of interactions with the environment: the remedy is error-correcting codes that reverse and undo the errors (Demski et al., 2006).

The Accounting Environment

An accounting system has its own environment (which consists of reporting units and their governance mechanisms, regulators, and standard setters) that interacts more intensively with the accounting measures with regard to fair value measures, compared to their historical cost (Demski et al., 2006).

In accounting information, information extraction and sharing is enhanced by standards that guide how accounting information is measured, disclosed and audited (Demski et al., 2006).

These accounting regulations are the product of the interaction among various stakeholders (Demski et al., 2006), namely regulators, reporting firms, investment groups and the political class, and derive from the synergy of accounting rules, procedures, key indicators and are influenced by information systems (Figure 5).

Similarly in quantum information is crucial the impact of the environment and how its interaction with the system shape data: in particular, quantum mechanical states can be viewed as extremely delicate, and any interaction of the system with the environment may destroy the information or change the system completely (Demski et al., 2006).

Anyway, while it is never possible to control or isolate an accounting system from its institutional settings, it may be possible to design an experiment so that the interaction between the quantum system and its environment is controlled.

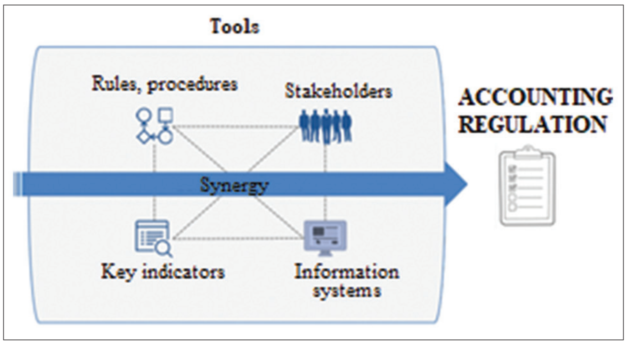

Figure 5: Synergies in the accounting domain. Source: author's elaboration

FINAL REMARKS OR THE REAL BEGINNING

As AI is becoming a key element of the business environment, this paper investigated extant relevant research on deep-learning-based LLMs and tried to disclose the main trust issues that have so far blocked their extensive adoption.

This study tries to determine how to keep the human relevant to limit the deskilling effect of knowledge-based systems, suggesting that the best strategy to integrate LLMs into large enterprises is the "human in the loop", as human experts have to validate AI-generated outputs to mitigate LLMs' risks.

This human-in-the-loop strategy can reduce LLM-related risks and leverage their potential to drive efficiency, growth and innovation (Rowdur, 2023).

Thus, the best way to include AI-generated insights appears to be that of recognising the significance of human expertise and fostering a culture of collaboration between AI and human teams.

Then, as big data sets provide new insights, improving decision-making and leading to better strategic business solutions, their management through data analytics requires new job skills due to their complex nature and large volume; in this sense, a successful adaptation to the constantly changing competence requirements requires lifelong learning, thus accounting professionals are challenged to build such skills through proper education and training (Stancheva-Todorova, 2018).

This paper also outlined a MSE Framework that enables to anticipate and take account of AI's impact at different scales and encourages the user to understand where the most focus for concern or action is needed.

Then, by discussing the ethical implications of AI, it emerged that accountants must use AI for the right purposes and processes during AI-based decision-making, considering the specific context and situation, taking into account and dialoguing with the stakeholders in decision-making processes.

Finally, to enrich our approach to accounting information we included a brief discussion on how the double- entry perspective of accounting can be enriched by the quantum perspective and the classical (non-quantum) perspective, as understanding quantum information may improve our understanding of accounting information and vice versa.

In this symbiotic relationship, dynamics and learning are ever present, as firms and managers, but also non-accounting actors, learn to respond to innovations (Demski et al., 2006).

In conclusion, companies will have to adopt AI in a continuous learning cycle considering that AI's greatest impact will be that of changing what people do, and hopefully this paper enriches the current understanding of AI to the point of encouraging the adoption of intelligent technologies in the accounting practice.

FUTURE RESEARCH

With the rapid advances in data analytics, machine learning, and continuous monitoring along with other related advances in artificial intelligence-based technologies that are providing us with the power to replace workers with automated systems, various other questions should be addressed including if there are ethical dilemmas associated with replacing humans (Sutton et al., 2018) and what are more broadly the ethical implications of the use of this emerging technology (Munoko et al., 2020).

Those studies will have to investigate a more mature stage of AI, as ethics represents a challenge arising in the post-adoption stage, and not every aspect of AI's impact on decision-making and managerial accounting can be observed immediately, but these may emerge only after years of use (Zhang et al., 2023).

Instead, future research on AI at the emerging level may be informed by case studies that generate information about best practices, to better understand the situation of the technology in organizations, while firms implement the technology.

Then, surveys or interviews with experts can be used to understand what is or is not working as the technology is introduced into organizations.

It's also important to investigate what is the role of accounting regulators and standards setting bodies and to stress the increasing need of their institutional support.

This considering that they have to consider the impact of the new technologies on financial reporting standards and provide transparency of the data outputs, derived by application of machine learning models, considering the risks associated with AI applications (Stancheva-Todorova, 2018).

Another open question is to comprehend whether automation is the most effective solution (Sutton et al., 2018), and research in this direction may lead to an alternative strategy that is to transfer knowledge to the user during the work process in order to retain human expertise and relevance in decision making.

Additionally, a salient extension would be to review previous empirical research and try to determine where the results were affected by biases, especially in the case of the so-called "productivity paradox", meaning that in the maturity and adoption curves are likely to occur greater productivity gains, at lower costs, as technology is less expensive (O'Leary, 2009).

Further, this same approach could be applied to certain accounting concepts, such as Sarbanes-Oxley, considering that these could present biases, just like it happens with technology, and these likely go through the same maturity and adoption curves (O'Leary, 2009).

All these streams of research will drive research forward and allow policymakers and managers to make informed decisions concerning organizational challenges and necessary adaptations (Lehner et al., 2022).

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