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How is generative artificial intelligence shaping the future of finance, accounting and investments in listed firms?

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Abstract

Generative artificial intelligence, machine learning, and blockchain technologies are rapidly transforming various industries, and finance, accounting, and investment fields are no exception, as they can affect how financial data is analyzed and interpreted. This paper discusses these innovative trends and their implications for listed companies. Guided by technology acceptance theory and technology readiness theory, the paper employed an integrative review methodology to identify emerging constructs related to these three fields. These technologies can revolutionize finance, accounting, and investment processes by enhancing big data analytics, accuracy, efficiency, fraud detection, risk assessment, forecasting, reporting, client engagement, and the identification of functional anomalies. Experts can then focus on value-added tasks and improved collaboration among professionals. Adoption of these technologies can enable listed firms to streamline financial operations, automate repetitive tasks, and focus on strategic financial decision-making processes. Data analytics and predictive modeling enable the extraction of valuable insights from large datasets, facilitating proactive financial decision-making and providing value-added services to clients. Practitioners must upskill to adapt to new technologies, become strategic advisors, and embrace sustainable practices to drive business success in such a dynamic environment. While financial regulators must review their policies, universities and professional development bodies need to redesign their training curricula.

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1. Introduction

Generative artificial intelligence (AI) has emerged as a transformative force across various sectors, reshaping traditional business practices and streamlining complex processes. The accounting, finance and investment profession, known for their meticulous attention to financial data and compliance, have embraced AI technologies to enhance efficiency, accuracy and decision-making (Stancu, 2021). By automating repetitive tasks, leveraging machine learning algorithms, and analyzing large datasets, generative AI can revolutionize the accounting and finance landscape (Sutton, Holt, & Arnold, 2016). The integration of AI technologies has the potential to propel these professions into a new era of productivity and innovation (Fox, 2018). According to Fox (2018) AI has the ability to help machines think, almost as a human being does. Its main approach is to gradually show how computers can perform human tasks and discover way to perform human actions (Chukwudi, 2018). This type of technology equips machines or computers to make predictions about operational issues and adjust them to boost corporate performance (Kirschner & Stoyanov, 2020).

With automation of routine tasks, enhanced data analysis, fraud detection capabilities, streamlined compliance, and predictive analytics, accounting and investment finance experts can provide more valuable insights and strategic support to their clients and organizations. Recently, for example, deep learning techniques – an advanced technique of machine learning based on artificial neural network algorithms – enabled anomaly detection, (deep anomaly detection) has emerged as a critical direction (Chai & Li, 2019; Pang, Shen, Cao, & Hengel, 2021) which can promote stock trading in securities markets. As AI continues to evolve, accounting and investment professionals must embrace these advancements to stay competitive, adapt to changing demands, and navigate the complexities of the modern financial landscape (Kovalenko et al., 2021). The accounting and finance profession can therefore significantly benefit from this technology as it is characterized by the fulfilment of tasks and continuous improvement of human capabilities (Carriço, 2018).

Artificial intelligence and machine learning – a branch of AI which utilizes plethora of statistical models to make predictions and enhance data accuracy – are therefore becoming more and more valuable tools in the fields of accounting and finance due to their capacity to quickly handle and evaluate enormous volumes of data. By using artificial intelligence, financial operations like fraud detection, risk management, and data forecasting are made more effective and efficient. The implication is that securities exchange listed firms that use these technologies – that will more thoroughly shape the world – have a very bright future (ICAEW, 2018; Wei, Li, Cao, Ou, & Chen, 2013). In this article, we discuss the current and future applications of artificial intelligence, machine learning technologies and large language models in accounting and finance, as well as their potential benefits to listed firms.

It is clear that there are many potentials of generative AI, yet inadequately discussed in the financial industry. The objective of this paper, therefore, was to explore the impact of generative AI on financial decision-making processes, risk management strategies, and investment trends to shed light on how the listed firms can leverage potential of AI to stay competitive and enhance operational efficiency. It achieves this by querying the transformative power of generative AI in the finance and investment landscape to stimulate discussions on best practices and frameworks for harnessing AI's full potential while mitigating associated challenges in finance, accounting and investments.

2. Theoretical Underpinning

Theoretical premises are an essential component of any study because they serve as the foundation upon which the research is built. These premises provide a framework for understanding the subject matter by providing the conceptual clarity, guiding the formulation of research questions or hypotheses, and contextualizing research methodologies and the findings (Waweru, Onyuma, & Murumba, 2021).

Our paper was guided by two theories. First, the technology acceptance theory championed by Fred in 1989. In his theory, Davis explained the psychological behaviour of information systems users (Davis, 1989) based on the attitude, belief, intention and user behavior relationship (Julianto & Yasa, 2019). This theory is particularly relevant for understanding the adoption and acceptance of AI technologies in the accounting, finance and investment professions. The theory contends that the intention to use a technology is shaped by at least four issues: perceived usefulness, perceived ease of use, and actual use in real behaviour in adapting to the technology (Julianto & Yasa, 2019). Perceived usefulness is the degree to which people believe that using a particular technology will enhance their job effectiveness and performance. On its part, perceived ease of use relates to the extent to which people believe that using a technology will be effortless and user-friendly (Taherdoost, 2018). This is so because individuals usually abhor new difficult-to-manoeuvre technologies.

Therefore, in the context of AI in the accounting, finance and investment professions, this theory provides information that helps to understand the variables that influence accountants, finance and investment advisors' willingness to embrace AI-driven solutions and how they perceive the influence of AI on their professional roles (Souza, Da Silva, & Ferreira, 2017). It also provides an analysis on the degree of acceptance and effective use of new digital technologies by professionals. However, accountants, finance and investment advisors are faced with difficulties in adapting to new technology which is expected to bring ease in their professions (Souza et al., 2017). By employing this theory, the paper can assess the drivers and barriers of AI technologies adoption in the accounting, finance and investment professions, offering insights into the factors that facilitate or hinder the integration of AI technologies in these fields. Additionally, the model guides the development of interventions and strategies to promote the successful implementation and acceptance of generative AI technologies in the accounting, financial and investments industry (Meiryani, 2021) particularly in the securities markets listed firms.

Secondly, the technology readiness theory assesses individuals' willingness and readiness to adopt and use new technologies. It was developed by Parasuraman (2000) and measures technology readiness based on four dimensions, namely: optimism, innovativeness, discomfort and insecurity. Technological readiness is the willingness and enthusiasm of a technology user in its application in the actualization of a task. Optimism measure the extent to which individuals believe that technology can make their work easier, more efficient, and effective. In the accounting and finance professions, optimistic accountants and investment finance advisors may view generative AI technologies as a tool that streamlines processes and improves accuracy in financial data management. On the other hand, innovativeness is the degree to which individuals are open to trying out new technologies and innovative solutions. In the context of generative AI adoption in accounting and finance, more innovative experts might be early adopters of AI-powered tools to gain a competitive advantage and explore new opportunities (Karger & Kureljusic, 2023). Discomfort is the level of discomfort or anxiety individuals experience when using new technologies. Some accounting, finance and investment experts may feel hesitant about generative AI adoption due to concerns about job security, technical challenges, or perceived complexity. Insecurity is the degree of perceived vulnerability when using technology. Accounting and investment professionals who feel insecure about their technical skills might be reluctant to adopt generative AI solutions, fearing they might not effectively operate or understand these new tools (Alkhaffaf, Idris, Abdullah, & Al-Aidaros, 2018).

Given that within financial industry listed firms are adopting a plethora of financial technologies (FinTech), and clients as well as investors are demanding quicker, more secure FinTech services, these professionals have no choice but to adopt the emerging financial technologies. By applying these theories in the context of generative AI adoption in accounting, finance and investments, researchers can identify experts' technology readiness levels, understand their attitudes towards AI, and predict their likelihood of adopting AI technologies in their work.

3. Methodology

This paper employed a systematic means of assembling and synthesizing previous research through an integrative review process of research with theoretical and empirical data (Whittemore & Knafl, 2005). The paper adopted a concept-centric rather than an author-centric approach (Webster & Watson, 2002) due to the inclusion of eleven streams of literature: generative artificial intelligence, automation of accounting and investments, Blockchain technology, big data analytics, compliance and reporting, data accuracy and quality, forensic accounting, financial forecasting, investment analysis, machine learning technology, and client engagement and advisory services.

A systematic review can be conducted using Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines, according to Briner and Denyer (2012). In the application of these guidelines, a guideline checklist was developed and followed to clearly indicate and describe the stages of article identification, selection, screening, eligibility criteria and inclusion.

Following Sewpersadh, Webster and Watson (2002) the research process started with a protocol development to create a defined body of literature for the theoretical analysis of a responsive corporate innovation adaptability. The protocol had three phases, in which phase one mitigated the incompleteness risk of the literature review by systematically identifying and reviewing existing databases: Elsevier (31), Springer Link (24), Emerald Journals (17), Wiley Online Library (12), Taylor and Francis (19), Science Direct (11), and Web of Science (15). The search was limited to studies published between 2010 and 2024. Overall, the search resulted in 128 articles identified through searching these databases. Whereas phase two remedied the overlap from different databases by filtering for duplicate articles, thus resulting in 115 articles screened by titles and abstracts selected, the last phase created a consistent structure among all patterns, in which there was rigorous screening and appraisal of each article to assess whether its content was fundamentally relevant to the themes of this study.

From a total of 115 papers, a final sample of 70 high-quality relevant articles was selected to build the theoretical constructs for the study. Other articles published by innovations, technology or accounting, or finance or investments firms in this paper's literature review and findings section were used to establish current market practices. The suppositions of the integrative review led to development of a nuanced conceptual discussion, thus a thematic analysis was used to consolidate further and conceptualize higher levels of themes, constructs, patterns and descriptions from articles associated with artificial intelligence, automation of accounting and investments, Blockchain technology, big data analytics, compliance and reporting, data accuracy and quality, forensic accounting, financial forecasting, investment analysis, machine learning technology, and client engagement and advisory services.

Being a thematic analysis, and by employing this approach, this paper has offered a structured approach to analyzing qualitative data by identifying patterns and themes to shed light on the research question to be investigated. It has, therefore, systematically examined and interpreted existing information, to uncover underlying meanings and relationships to provide valuable insights into the phenomenon under investigation. Through the application of this method, the paper has pointed out a number of research blind spots and provided policy Implications.

4. Findings from Systematic Review

The noted impact of high-level artificial intelligence has the potential to address plethora of high-end accounting, finance and investment issues in listed companies. The discussion of findings in this paper is therefore made highlighting, first on facets (Arslanian & Fischer, 2019; Cao, 2020, 2022a; Karger & Kureljusic, 2023; Tkáč & Verner, 2016): financial modelling, financial analysis and forecasting, financial event analysis, financial behaviour insight, financial compliance and risk management, financial planning, financial optimization, and financial innovations. Secondly, the discussion of the review findings is also performed based on the following highpoints (Kovalenko et al., 2021; Reckord, 2020; Souza et al., 2017; Stancu, 2021; Sung, 2021; Taha, 2020): accounting and financial anomaly detection, accounting and investments ethics assurance. accounting and financial representations, accounting and financial simulations, accounting and financial computing, accounting and financial prediction, financial recommendation and intervention, accounting and financial intelligent systems, accounting and financial intelligent services, accounting and financial visualization, and accounting and financial security assurance.

4.1. Adoption of Generative Artificial Intelligence by Listed Firms

In accounting and investment finance, generative artificial intelligence and machine learning are making significant strides. With the advent of big data and the increasing amount of digital information, artificial intelligence and machine learning have become critical tools for quickly and accurately analyzing vast amounts of financial data. So, what changes will these two major technologies bring that will shape the future of finance and accounting sectors?

The emergence of the Covid-19 Pandemic opened a new window behind accounting and finance industry, and many listed firms have been surveying the damage and building models of how to cope and recover. For those who have survived, they are wondering what is next. Will there be another pandemic? If so, will it be as devastating as the Covid-19, or has the industry entered the new normal phase of the pandemic? For firms that survived the Pandemic, now need to thrive, by fully getting back to business. Although investments, sales or product demand may not return to pre- Pandemic levels anytime soon, getting back to business means such listed firms still needs to plan, analyze, and invest in key initiatives if they want to financially thrive and grow. That is exactly why finance managers in medium-to-large listed firm must keep their sights set on finding value from AI technologies such as machine learning and predictive analytics. Therefore, if these managers want to see adoption of such technologies in finance go mainstream, they have to think differently (Cao, 2022a; Stern, 2020).

To evaluate the value of advanced analytics, finance teams should ask themselves whether they want to spend time building models or interacting with forecast models? Advanced analytics in finance is similar to other corporate performance management processes such as planning, financial consolidation and reporting. If finance teams spend all of their time moving data, reconciling data and building reports, they will have no time to leverage this data to guide key financial decisions (Marr, 2020). By leveraging technology to handle the hard work, finance teams can shift a larger portion of their time to value-driving activities, such as forecasting cash or evaluating key capital investment decisions. In doing so, accounting, finance and investment teams will be stepping forward, as they have throughout various crises, to unleash their true potential as strategic business and investment partners.

Granted, creating value from advanced analytics in finance requires a similar approach. Within financial management and investment processes, advanced analytics can play a powerful role in driving collaboration and effective decision-making. Consider the corporate performance management framework, as suggested by OneStream (2020) which involve goal setting, modelling, planning, operational analysis, consolidation and closure, reporting, and analysis, and then start all-over again. Whichever the version of this framework, they all most consistently show the role strategic finance plays in steering firm performance as a continuous cycle of mapping key strategies into actionable business plans.

A survey conducted by OneStream (2020) adoption of AI technologies – especially machine learning tools – in finance was already at 14 percent, while 35 percent of the firms indicated they were in the process of their use in accounting, finance and investment. It seems most finance teams do not have the skillsets and/or tools to quickly develop statistically significant and insightful models, integrate them directly into planning and analysis processes, and do it at reasonable scale.

The following four questions can be used to support this view. For instance, when a firm's finance team meets with the board/executive team, do they have any perspective on how its products or services are impacted by external factors? When the finance team set targets for consolidated company or divisional plans, are the targets based on gut feel, or do they consider historical performance and external factors such as economic growth, consumer preferences, or energy prices, and global financial market trends? Are firm's forecast models accommodating the potential impact from competitor actions such as pricing changes or new product and investment additions? Lastly, during annual financial planning or forecasting processes, does the firm work in real-time with sales, operations, and other functions to understand the why behind bottom-up forecasting to test the numbers?

This is where the advanced analytics should enter the corporate financial performance management equation. Like the increased adoption of cloud-based solutions by finance teams, the adoption of predictive analytics and ML is a matter of when – not if. For example, when asked whether they were using AI techniques – especially predicting analytics tools – in finance the results from a recent industry survey by OneStream (2020) indicate that already the application is at 16 percent, while 40 percent of the firms indicated they were considering or evaluating the use of the tools in corporate finance.

A more recent survey by OneStream Software, a leader in corporate performance management solutions for the world's leading firms, published its Enterprise Financial Decision-Makers Outlook (April 2023) semi-annual survey. Conducted by Hanover Research, the survey targeted finance, accounting and investment leaders across North America (United States, Canada and Mexico) to identify trends and investment priorities in response to economic challenges and other forces in the upcoming year. It sourced insights from 516 finance decision makers holding a management position including chief finance officers, director and controller.

The results of the survey indicate that analytic technologies are gaining focus to help navigate corporate uncertainty. In fact, trends in the OneStream (2023) survey foreshadow an increased usage of analytic technologies that improves productivity and supports more agile decision-making across the enterprise. Cloud-based planning and reporting solutions remain the most used data analysis tool (91%), however, most firms also use predictive analytics (85%), business intelligence (84%) and ML/AI (75%) tools at least intermittently. About half of the firms were planning to invest more in each of these tools in 2023, compared to 2022. Admittedly, the adoption momentum for these tools started during the Corona pandemic with no sign of slowing down. According to the 2021 survey, firms reported that in comparison to pre-pandemic they were increasing investments in artificial intelligence (59%), predictive analytics (58%), cloud-based planning and reporting solutions (57%) and machine learning (54%).

From the above survey, firms seem to be realizing the value of generative AI, since according to the survey, two-thirds of the firms (68%) have adopted an automated machine learning (AutoML) solution to supplement some of their workforce needs, a significant uptick when compared to 2022 survey (56%). In the 2022 survey, 48 percent of respondents planned to investigate an AutoML solution in the future, which suggests respondents stayed true to their word and dove in on these technologies. Therefore, finance and accounting leaders see opportunities for improvement in many areas with the help of ML/AI technologies, including ChatGPT and ChatCSV. The tasks and processes they believe these technologies will be most useful for include auditing, accounting and financial reporting, financial planning and analysis, sales/revenue forecasting, sales and marketing, and customer service.

Along with investing in new technology, almost all the firms (91%) in the OneStream (2023) survey were investing or planned to invest in new solutions that specifically support finance, accounting and investment functions. The most common solutions are cloud-based applications (52%), AI/ML (43%), advanced predictive analytics (42%) and budgeting/planning systems (42%). In fact, about 46 percent of firms currently have at least one generative AI project under development. In order to thrive in the cutthroat market, we believe that this ratio will rise in the upcoming years, particularly in developing and emerging markets.

With the sheer volume of data available and advancements in corporate performance financial management software, finance teams now – finally – have the capabilities to interact with advanced analytics and do it at scale. How? Instead of taking on the burden of building models, finance teams can rely on purpose-built software to help them supplement their planning processes with statistically significant, predictive forecasts to compare against manager-driven forecasts that may be biased by the fog of uncertainty. Granted, how should firms begin this journey? Finance, accounting and investment teams should consider advanced analytics as part of a broader framework that includes predictive analytics and machine learning – all aimed at achieving low cost and high value.

Predictive analytics provides the power to predict future corporate performance based on applying predictive algorithms to historical data. Although such application is not entirely new, by automating model creation and deployment directly within corporate financial performance management processes, predictive modelling is easy to execute for any corporate planner. This ease of use makes predictive models incredibly powerful for finance teams, especially when they can directly leverage predictive models or combine a baseline predictive forecast with specific business initiatives (Stern, 2020). However, no predictive algorithm is going to predict with complete accuracy since human intuition and business acumen still play a role, after all.

For finance, accounting and investment practitioners who need to go beyond traditional predictive analytics, machine learning seems to be the answer. Machine learning is where people and technology come together. For example, consider a retailer's demand forecast for product X in region Y within store Z. To forecast at this granular level, there are so many other factors that come to the equation. How about the weather in region Y, for instance? And what if store Z built a new parking space? Or what if a major competitor opens a location across the street or materially changes pricing? Factors such as these are all potential features a machine learning model might consider if a listed firm's finance team has made the necessary investments in data scientists.

Nonetheless, the ability of generative artificial intelligence and machine learning to provide fast and accurate financial analysis have the greatest impact on economics-related fields. By identifying patterns and making predictions, machine learning algorithms can quickly analyze large amounts of financial data (McKinsey, 2020). Such algorithms, for example, can predict the likelihood of a loan default based on a variety of factors such as credit scores, income levels, and work history. Similarly, other generative AI algorithms can be used to manage risk, too. These algorithms can also analyze financial data to identify potential risks like fraud in banks, insurance, stockbroking firms or securities market volatility. Such generative AIs can also be used to create various stock trading strategies and optimize portfolios.

It is evident that finance, accounting and investment processes and investments is being transformed by generative AI and machine learning. These technologies, with their ability to analyze large amounts of data quickly and accurately, can automate many mundane finance, accounting and investment -related tasks such as data entry, reconciliation and asset valuations (OECD, 2020). Patterns and anomalies in financial data can also be identified using ML algorithms. They can, for example, detect unusual transactions that may indicate fraudulent activity like in banks and stockbroking firms. Generative AI can also be used to streamline the audit process, allowing auditors to focus on high-risk areas and reducing the need for manual review. This will enhance the current push for risk-based auditing and financial market supervision.

The generative AI such as ML algorithms automatically evaluate vast amounts of data, lowering the chance of errors and producing data that is more dependable and accurate. Many routine financial, investments and accounting-related procedures can be automated to save time and free up staff members to work on more challenging and strategic projects. In addition, the insights and analytics provided by generative AIs like ML can help make decisions more effectively, and automating many tasks can reduce manual labour costs and increase productivity (OECD, 2021) thereby improving firm profitability and shareholder returns.

Indeed, it appears that ML and other generative AIs are revolutionizing how finance, accounting and investment professionals examine data, make judgments, and complete tasks. Even though there are some difficulties in using these emerging technologies, the accuracy gains, time savings, and improved decision-making they provide make them a crucial decision for businesses trying to maintain their competitiveness in the modern digital age. Compared to predictive analytics, ML comes at a higher cost and is harder to scale, but if a firm is committed to the investment, there's a higher reward in terms of forecast accuracy (Govil, 2020). Ultimately, it is not a question of whether predictive analytics or machine learning is better or worse than the other. The bigger and more important point for listed corporate finance teams is to know what they are trying to achieve with advanced analytics and then select the right technique to do so.

Generative AI can therefore revolutionize the finance, accounting and investment profession in several ways. From the findings of the study the different ways are as discussed below.

4.2. Data Automation and Efficiency

Artificial intelligence (AI) has significantly transformed the finance, accounting and investment profession, revolutionizing traditional processes and enhancing efficiency. The tradition accounting and investment procedures have been faced with lack of security (Ash, 2020). This factor has led to the adoption of automated accounting and finance functions. The areas of auditing, accountancy, and book-keeping face a 98 percent possibility of automation due to the increasing need for efficiency and transparency in firms (Taha, 2020). People can only function efficiently for a limited amount of time and cannot sustain a constant standard of success during the day (Gardner, 2019). Human beings have a tendency to get tired unlike technology. By leveraging machine learning algorithms, accountants can automate data entry, processing, and analysis, streamlining workflows and improving accuracy. Manual data entry and transaction processing are time-consuming and prone to errors.

Some generative AI tools, such as optical character recognition as well as robotic process automation, automate data extraction, categorization, entry and analysis, thus significantly reducing human effort and increasing accuracy by minimizing mistakes (Botkeeper, 2020). These technologies have the potential of freeing up accountants' time, allowing them to focus on higher-value activities such as data analysis and strategic decision-making. Generative AI's ability to automate repetitive and time-consuming tasks in accounting has been widely acknowledged as a game-changer for the industry (Ash, 2020). Such character recognition systems, capable of extracting information from physical documents and converting them into digital formats, do automate the cumbersome task of manual data entry. According to a study by Deloitte, such character recognition technology can achieve accuracy rates of up to 99 percent, thereby significantly improving data quality and reliability (Deloitte, 2021). Therefore, generative AI and other automation technologies have the potential of automating up to 43 percent of finance, accounting and investment activities, ranging from data entry to accounts payable and receivable processes (McKinsey Global Institute, 2018) and investments portfolio analysis (Karger & Kureljusic, 2023). Such Generative AI abilities can therefore reduce audit efforts and well as the need for deeper financial market surveillance and other forms of regulation.

4.3. Enhanced Data Accuracy and Quality

Conventional finance, accounting and investment analysis procedures have the problem of coping with huge amount of data, with the potential of affecting the quality of such data (Oussous, Benjelloun, Lahcen, & Belfkih, 2018). Generative AI technologies play a crucial role in data cleansing and error detection, leading to improved data accuracy. In addition, machine learning algorithms can identify and rectify inconsistencies, outliers, and missing values in datasets of listed finance, accounting and investment firms. By analyzing patterns and relationships within the data, Generative AI algorithms can detect errors and suggest appropriate corrections (Rahmani et al., 2021). This ensures that data is clean, reliable, and suitable for analysis. Such AI-driven data cleansing techniques achieves higher accuracy rates in error detection compared to traditional methods (Abebe, Kleinberg, & Levy, 2019). Through pattern recognition and machine learning, AI algorithms can validate data against predefined rules, standards, and reference datasets. Furthermore, AI-powered algorithms can compare customer or investor records against known fraud patterns or perform real-time data validation during transaction processing. This significantly reduces the risk of erroneous data entry and enhances data accuracy. A report by Gartner emphasizes the importance of generative AI in automating data validation and verification processes (Gardner, 2019).

Moreover, data enrichment and augmentation has been great milestone to data accuracy. Both large language models and natural language processing algorithms can analyze unstructured text and extract valuable information to enhance structured financial datasets (Bansal, Chen, Tam, Raffel, & Yang, 2018). By automatically annotating data with relevant metadata, generative AI algorithms can thus improve data categorization, completeness, and accuracy. Furthermore, generative AI can leverage external data sources and integrate them with internal datasets, providing additional context and enhancing the overall quality of the information. Generative AI has demonstrated the effectiveness of AI in data augmentation for improved accuracy (Bansal et al., 2018).

Continuous Learning and Adaptive Algorithms have the ability to continuously learn and adapt to new data, leading to improved data accuracy over time. According to Mahajan and Rathi (2018) machine learning models can analyze patterns, trends, and feedback from user interactions to refine their predictions and improve the accuracy of data processing tasks. As the generative AI algorithms encounter new data, they update their knowledge and adjust their behavior, reducing errors and enhancing accuracy for listed firms. This adaptive capability of AI algorithms ensures that data accuracy remains high, even in dynamic and evolving environments. This leads to 70 percent reduction in data related errors in the accounting process (Mahajan & Rathi, 2018).

4.4. Streamlined Workflows and Time-Saving

Available evidence points to the fact that artificial intelligence has proven to be a powerful tool in streamlining workflows and saving time through task automation, intelligent data processing, optimization, and proactive decision-making (Reckord, 2020). Through leveraging generative AI technologies, securities market listed firms can improve efficiency, reduce human effort, and make data-driven decisions faster (Dyrsmid, 2023). In addition, through such automation of many repetitive tasks, improving efficiency, and providing intelligent insights, AI technologies have become invaluable tools in optimizing workflows (Dyrsmid, 2023). In fact, machine learning algorithms can be trained to perform financial tasks such as data entry, document processing, and report generation, reducing human effort and potential errors. This kind of process automation can improve workflow efficiency and allows employees to focus on higher-value activities (PixelPlex, 2020). A study conducted by McKinsey (2020) estimated that automation technologies, including generative AI, could save employees up to 20 percent of their working time. On its part, machine learning algorithms can extract insights, identify patterns, and make predictions, enabling efficient decision-making. By leveraging AI in data processing, workflows can be streamlined by reducing manual data analysis and interpretation (Hutchinson, Bramwell, Bramwell, Gonzalez, & Gonzalez, 2019). For example, generative AI-powered Chatbots can understand and respond to customer queries, improving customer service efficiency in listed firms. A study published in 2020 demonstrated that generative AI-based data processing reduced the time required for financial data analysis by up to 90 percent (Lemaire, Dupont, & Lefebvre, 2020).

AI algorithms can also optimize workflows by intelligently allocating resources and prioritizing tasks. By analyzing historical data, real-time demand, and other relevant factors, generative AI technologies can generate optimized schedules, task assignments, and resource allocations (Varshneya, 2021). This streamlines the workflow, reduces bottlenecks, and maximizes productivity. Moreover, generative AI-driven project management tools can optimize task dependencies, deadlines, and resource utilization, enhancing overall project efficiency. Existing evidence show that AI-based optimization techniques improved workflow efficiency by up to 25 percent (Wang, Zhang, & Li, 2019). By facilitating predictive maintenance and proactive decision-making, AI facilitates can enable listed firms to proactively address equipment failures and reduce downtime. By analyzing sensor data, historical maintenance records, and other relevant parameters, AI algorithms can predict maintenance needs and provide early warnings. This allows firms to schedule maintenance activities strategically, reducing unplanned disruptions and saving time (Rana, 2020). generative AI technologies also support proactive decision-making by analyzing financial data and providing recommendations in real-time, ensuring timely actions and preventing potential delays (Varshneya, 2021). This becomes handy in listing firms' environment, where deadlines for production and submission of final financial reports to regulators are strict.

4.5. Streamlining Compliance and Financial Reporting

Compliance with accounting standards and listing firms' regulations is a critical aspect of the accounting and finance professions. Generative AI has significantly streamlined this process by automating the preparation and validation of financial reports. Cloud-based solutions are gaining popularity, as they enable listed firms to store and access data from anywhere in the world. Generative AI technologies streamline financial reporting processes by automating data aggregation, analysis, and report generation. Machine learning algorithms can extract financial data from various sources, perform calculations, and generate accurate and timely accounting and financial reports. This automation eliminates manual efforts, reduces errors, and improves financial reporting efficiency (Das, 2020). Moreover, many AI-powered reporting systems ensure compliance with regulatory standards by automatically validating financial data against established rules and guidelines. AI-based financial reporting systems improve accuracy and reduced reporting time by up to 70 percent (Das, 2020).

A report by Deloitte emphasizes that AI-driven analytics tools provide organizations with real-time insights, enabling proactive decision-making (Deloitte, 2021). In essence, generative AI enables intelligent data analysis and generates actionable insights from financial data. On its part, machine learning algorithms can identify patterns, correlations, and anomalies in large datasets, providing valuable insights into financial performance, market trends, and customer behavior. By leveraging AI for data analysis, listed firms can identify growth opportunities, optimize costs, and mitigate risks. For example, generative AI algorithms can analyze historical financial data and predict future cash flow patterns, assisting such firms in making informed financial decisions (OECD, 2021).

Financial fraud has become a major impediment in many organizations. It is a major global problem affecting most organizations. Fraud is often undetected and never reported, making it difficult to determine the full scope of global losses (Firmansyah, 2022). Data analytics is closely related to artificial intelligence. The tools used in data analytics are also used in artificial intelligence. Machine learning models can analyze vast amounts of financial data and identify patterns indicative of fraudulent behaviour, enabling accountants and finance professionals to detect and prevent potential fraud. Additionally, AI-based risk assessment models help these experts to evaluate and mitigate risks by analyzing historical data, market trends, and other relevant factors, providing valuable insights for informed decision-making. Moreover, AI's sophisticated algorithms have proven to be highly effective in detecting fraudulent activities and mitigating risks in financial transactions. A survey by KPMG indicates that about 70 percent of financial institutions are using AI for fraud detection, attributing its success to its ability to analyze large datasets and identify suspicious patterns in real-time (KPMG, 2021). By proactively detecting potential fraud, finance, accounting and investment professional can protect their clients' financial interests and strengthen their listed firms' overall security.

The machine learning models can analyze large volumes of financial data, identify patterns indicative of fraudulent activities, and highlight areas of potential risk (Cao, 2022b). By continuously learning from new data, AI algorithms can adapt and improve fraud detection and risk assessment over time. This can significantly reduce false positives and detect fraudulent behaviours that might be missed by traditional methods. Generative AI algorithms have been proved to achieve a 96 percent accuracy rate in fraud detection compared to traditional methods (Hasan, 2021; Phua, Lee, Smith, & Gayler, 2020).

Similarly, listed firms require accurate information for informed decision making (Sanjiwani, Wulandari, Dewi, & Renta, 2024). Generative AI technologies can transform financial forecasting by leveraging predictive analytics capabilities. Also, AI can analyze historical financial data, market trends, and other relevant factors to generate accurate and reliable financial projections usually needed by shareholders. AI-powered forecasting models has the potential of adapting to changing conditions, enabling listed firms to make informed decisions regarding budgeting, investments, and resource allocation. The use of AI in financial forecasting can reduce biases, improves accuracy, and provide real-time updates based on changing market dynamics and improves accuracy by up to 20 percent compared to traditional methods (PwC, 2020).

4.6. Transforming Client Engagement and Advisory Services

Customer loyalty is another area where generative AI can become instrumental, especially in financial advisory firms. This is so since generative artificial intelligence can transform client financial engagement and advisory services by providing instant support, personalized experiences, data-driven insights, and collaborative decision-making. For instance, AI-driven Chatbots and virtual assistants can transform client engagement by providing instant, personalized support. The natural language processing algorithms enable Chatbots to understand and respond to client inquiries, improving responsiveness and customer satisfaction (Sung, 2021). Virtual assistants powered by generative AI can offer investment recommendations, answer frequently asked questions, and provide real-time investor support. These AI-powered solutions can therefore enhance client engagement by providing 24/7 availability and immediate responses to client queries (Foscht, Maloles, & Silva, 2021). This personalization enhances client satisfaction and strengthens the client-advisor relationship (Accenture, 2020) thereby cementing customer loyalty.

Additionally, AI technologies provide data-driven insights and recommendations, empowering advisors to offer valuable guidance to their clients. Large volumes of financial data, market trends, and client profiles can therefore be analyzed to identify opportunities, risks, and optimal strategies. This can lead to generation of real-time reports, interactive dashboards, and customized recommendations, thus enabling advisors to make informed decisions and provide tailored advice (EY, 2020). Collaborative decision-making is facilitated between clients and advisors. AI algorithms can therefore generate scenario-based analyses and simulate the potential outcomes of different strategies, thereby enabling clients to make well-informed decisions. This collaborative approach builds trust, enhances client satisfaction, and ensures alignment between clients' goals and recommended strategies (Sung, 2021).

4.7. Enhancing Credit Screening and Investment Decision Making

Generative AIs such as deep learning can be applicable in finance, banking and securities markets in a number of ways including portfolio construction and trading (Almahdi & Yang, 2017; Cavalcante, Brasileiro, Souza, Nobrega, & Oliveira, 2016) portfolio selection (Song, Liu, & Yang, 2017) macroeconomic prediction (Jeong & Kim, 2019) prediction of financial crises (Fischer & Krauss, 2018) and exchange rate predictions (Galeshchuk & Mukherjee, 2017; Sevim, Oztekin, Bali, Gumus, & Guresen, 2014). These can be instrumental in facilitating informed investment decision making ensuring high investor returns, with minimized investment risk.

Similarly, deep learning can also enhance securities market prediction (Chen et al., 2018; Singh & Srivastava, 2017) extrapolate market crisis (Chatzis, Siakoulis, Petropoulos, Stavroulakis, & Vlachogiannakis, 2018) facilitating securities trading volatility (Gunduz, Yaslan, & Cataltepe, 2017; Kim & Won, 2018; Sezer, Ozbayoglu, & Dogdu, 2017) enable securities market analysis (Chong, Han, & Park, 2017) and enhance market making quotation (Hsu, Chou, Huang, & Chen, 2018). Other include undertaking financial market sentiment analysis (Sohangir, Wang, Pomeranets, & Khoshgoftaar, 2018) identifying market manipulations (Martinez-Miranda, McBurney, & Howard, 2016) mining market information from data bases (Matsubara, Akita, & Uehara, 2018). These can facilitate sound investment decisions by investors and financial analysts.

In banks and credit card firms, deep learning can be instrumental in loan default risk analysis (Jurgovsky et al., 2018) and credit screening (Wang et al., 2019) consumer credit scoring (Butaru et al., 2016; Zhu, Yang, Wang, & Yuan, 2018) and bankruptcy prediction (Tadaaki, 2019) thereby enabling sound loaning decisions to prevent cases of bad debts.

4.8. Enhancing Financial Data Analytics

Rapid innovations of digital technologies is leading to fast growing in the volume of digital data (Klein, 2017). Large quantities of data are created from lots of sources such as social networks, smartphones, sensors, etc. Such huge amounts of data that conventional relational databases and analytical techniques are unable to store development of novel tools and analytical techniques are therefore required to discover patterns from large datasets. Big data is produced quickly from numerous sources in multiple formats. Henceforth, the novel analytical tools should be able to detect correlations between rapidly changing streams of financial data to better exploit them (Rahmani et al., 2021). The generative AI-powered algorithms can thus enhance the efficiency and accuracy of data analysis tasks, allow listed firms to derive meaningful insights from their financial data, automation of repetitive task, and process large datasets in a fraction of the time it would take a human analyst. This can tremendously save time and resources (Gardner, 2019).

Finally, financial analysts can focus on higher-level tasks that require human expertise. A report by Deloitte reveals that in developed economies, about 69 percent of finance leaders are already using AI for financial analysis and forecasting, leveraging its capabilities to identify trends, patterns, and anomalies in vast amounts of financial data (Deloitte, 2021). This type of data-driven approach can therefore enable accountants and other finance experts to provide more accurate financial advice and make informed decisions for their clients as well as their listed firms.

Given the above analysis and synthesis, what does this mean for securities market listed corporate finance and accounting teams? It should not be construed that the arguments in this paper imply that all of today's corporate accounting and financial decisions will be automated away. Also, corporate accounting, finance and investment professionals should not expect complete forecast accuracy all of the time. Moreover, we also do not from an argument that all legacy listed corporate planning processes should stop. The basic truth is that advanced analytics offers finance and accounting practitioners a new way to ask why, and there is nothing bad about having an unbiased forecast scenario to help drive dialogue with other business partners.

In fact, the arguments here have basically explained why corporate accounting, finance and investment experts need to shift focus from building advanced models to engaging with forecasting models, the key differences between predictive analytics and machine learning, and how accounting, finance and investment professionals can finally increase adoption and return on investments into advanced analytics. However, as it is with any other new technique or technology, it is critical for listed firms to shift through the current innovation hypes and try to understand what this means for them. No solution will offer the perfect forecast or answer every question that top management ask. However, if they take baby steps forward to evaluate advanced analytics through the lens of being an enabler for accounting, finance and investments rather than being yet another burden, securities market listed firms will take a giant leap forward into this post pandemic world. And management just might set up their firms to thrive too.

The other implication is that the current economic headwinds have finance, investments and accounting leaders acutely aware of their investment decisions and weighing the benefits compared to the costs. With revenue growth through economic uncertainty in mind, accounting, financial and investment managers are looking to invest in new technological solutions that can support more agile financial and investment decision-making, while delivering a fast return on investment. The generative AI innovations that have emerged in the last couple of years have the potential to improve the speed and accuracy of financial forecasting and support more informed, confident accounting, financial and investment decision making.

5. Conclusion and Policy Implications

The systematic review has presented a comprehensive view of AI-enabled modern finance, accounting and investment. The era of big data and intelligence-driven accounting and finance is being driven by the new generation of AI and Fintechs, particularly data science, deep learning, and machine learning. These technologies present vast opportunities for translating traditional accounting and financial theories, research, and models and promoting clever and intelligent finance, accounting and investment practices. They also further advance generative AIs to better tackle significant accounting and financial challenges and complexities in real-life and deliver actionable intelligence-driven accounting and investment finance as undertaken in the listed firms.

It should be noted that the impact of generative AIs on accounting, finance and investment profession is nothing short of revolutionary. From automating repetitive tasks to providing valuable insights for strategic decision, generative AI system can elevate the role of accountants, finance and investment professionals in listed firms to new heights. The potential efficiency gains and reduction in human error brought about by these tools can not only streamline processes but also allow these professionals to focus on more value-added business activities. As the accounting, finance and investment landscape continues to evolve, embracing generative AI is no longer an option but a necessity for securities market listed companies to remain competitive and relevant in today's data-driven world.

However, while generative AIs holds immense promise, its successful integration requires a balanced approach that combines technological advancements with the expertise and judgment of skilled accounting and finance professionals. By harnessing the power of generative AIs while upholding the core principles of accuracy and integrity, the accounting and finance professions can continue its transformation journey, embracing the future with confidence and adaptability.

This transformation is not without its challenges. ethical considerations, the need for continuous up-skilling, and the potential displacement of certain roles are factors that must be managed thoughtfully. The success of this revolution therefore hinges on the ability to harness AI as a powerful tool, rather than as a replacement for human judgment. As generative AIs further embeds itself into the core of accounting and financial practices, professionals must embrace the role of lifelong learners, adapting and augmenting their skills to collaborate seamlessly with the intelligent algorithms. The true promise of this revolution lies not just in efficient financial number-crunching but in the elevation of the role of these professionals as strategic partners in guiding businesses through a complex and ever-evolving financial landscape.

In the journey toward this generative AI-augmented future, it is paramount to remember that while the technology can facilitate remarkable achievements, it is the human ingenuity that envisions the possibilities and steers the course. The fusion of human intellect and artificial intelligence is propelling accounting and finance into uncharted territories, where the potential for innovation and insight knows no bounds. As the chisel to a sculptor or the brush to a painter, AI is becoming the indispensable instrument to the modern accountants and investment professionals, redefining their artistry and reshaping the canvas of accounting and finance.

The findings have a number of policy implications that could be advantageous for practitioners given the increased potential relevance of artificial intelligence in the field accounting and finance. This paper has given an overview of the many potential applications of generative AI algorithms in finance, investments, accounting and auditing in listed firms. Listed firms can assess which AI algorithms best fit their real-world requirements by using the results. Secondly, the outcomes can serve as a standard for forecast accuracy that accountants and finance professionals might aim for. The paper has also pointed out a number of research blind spots, including making sure that machine learning algorithms are accepted in listed firms. Nonetheless, listed firms must consider the many issues raised when integrating generative AI into operations of financial and non-financial firms' accounting and finance divisions.

Moreover, listed firms should focus on generative AI and large language models as these are the next evolution of AI given that they hold great promise in revolutionizing the accounting and finance sectors by automating routine tasks, increasing efficiency, and providing valuable insights. These models can therefore process large volumes of accounting and financial data, pull out relevant insights, and generate comprehensive accounting and other financial reports in a fraction of the time it would take for manual human processing, by leveraging natural language processing capabilities. This calls for major investments to be channeled in development and implementation of generative AI capabilities and cloud services within the financial sector. However, there remain complexities and challenges of training and improving large language models and the potential risks of generative AIs. This is so given that accuracy and reliability of these models cannot be assumed to be stable as they develop. Specific capabilities may even deteriorate as models continue to train due to the hundreds of billions of parameters used. Therefore, there exist fundamental and technical limitations of models and emphasized the importance of asking these tools the right financial questions and having mechanisms to identify mistakes when, and not if, they occur.

Furthermore, it is crucial to be aware of their limitations, such as the need for human judgment, data security concerns, and regulatory challenges. Successful applicability will require some evaluations to judge whether their adoption works well in particular finance, accounting and auditing domain (Huang, Chai, & Cho, 2020). This is because there are potential problems of over-fitting or under-fitting (Baek & Kim, 2018) and sustainability of these models (Bao, Yue, & Rao, 2017). By understanding and addressing these limitations, generative AIs, such as ML, DL and LLMs can be effectively integrated into finance, accounting, and investment practices, paving the way for a more efficient and insightful financial future in developing and emerging financial markets.

Finally, serious preparation is indispensable on the part of educators, financial regulators and professional examining bodies to be able to deal with these emerging paradigm shift and preparing the learners, policies and future professionals for corporate and market challenges in business and investment environment fraught with big data, Blockchain technology, machine learning, artificial intelligence, deep learning, large language learning models, etcetera. Universities will have to review their accounting, auditing and financial investment curriculum, while these examining bodies have to redesign their professional development and training courses. Also, financial regulators must formulate revolutionary market policies.

It seems that, in future, professional hybrids – cutting across these disciplines and technologies– are likely to emerge. Generative AI development and implementation in finance and investments, accounting and auditing professions, therefore, seem to be a double-edged sword. These professions as we know them today are in future going to fundamentally change as generative AI technologies emerge and develop to shape corporate and financial market practices. This paper contributes to literature by presenting a valuable accumulation of knowledge on related studies and providing useful recommendations for accountants, financial and investment analysts, financial market regulators, and researchers.

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